

ECOLOGICALLY INSPIRED REFINEMENT OF ENGINEERED SYSTEMS

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The Academic Faculty

by

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ECOLOGICALLY INSPIRED REFINEMENT OF ENGINEERED SYSTEMS

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In memory of my little brother, Andrew Malone.

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TABLE OF CONTENTS

ACKNOWLEDGEMENTS	iv
LIST OF TABLES	ix
LIST OF FIGURES	xiii
LIST OF SYMBOLS AND ABBREVIATIONS	xix
SUMMARY	xxii
CHAPTER 1. Introduction	1
1.1 Motivation	1
1.2 Ecological Systems Inspiration and Integration into Designed Systems	4
1.3 The Mission and Potential Impacts of This Research to Address Current Knowledge Gaps	6
1.4 Overall Research Question	8
1.5 Research Goals	8
1.5.1 Apply statistical methods to identify the key ENA metrics of ecological systems that most succinctly describe ecosystem performance.	8
1.5.2 Create a repository of biological, technological, or hybrid interventions that mimic the decomposer functional role in natural ecosystems	9
1.5.3 Create and apply a generalized ENA-based design methodology for the model-based design of engineered systems	9
1.6 Fundamental Research Contributions	10
1.6.1 Uncovering the Fundamental Differences in Structural and Flow-Based Configurations in Ecosystems as Compared to Engineered Systems	10
1.6.2 Broadening Current Research in the Field of Industrial Ecology	10
1.6.3 A Quantifiable and Adaptable Design Framework for Performing ENA Analysis in Engineered Systems	11
1.7 Research Tasks	11
1.8 Research Limitations and Assumptions	16
1.9 Dissertation Layout	17
1.10 In Summary	18
CHAPTER 2. Literature Review	20
2.1 Sustainable Development in the Engineered World	20
2.2 Organizing Principles of Ecosystems	23
2.2.1 Evolution and Sustainability in Food Webs	23
2.2.2 The Importance of Detrital Actors and the Decomposer Functional Role in Ecosystems	25
2.3 Graph Theory – Principles and Applications in Ecology and Engineered Networks	26

2.3.1	Principles of Graph Theory	26
2.3.2	Ecological Network Analysis (ENA)	28
2.3.3	Previous Ecological or Bio-Inspired Design Applications to Engineered Systems in Literature	35
2.4	Summary of Literature Review	39
 CHAPTER 3. Patterns in Ecosystems: Functional Understanding and Measurement 40		
3.1	Research Tasks and Goals to be Addressed	41
3.2	Ecosystems from Ecobase	41
3.2.1	Network Extraction and Balancing	42
3.3	Multivariate Methods for Ecosystem Functioning	43
3.3.1	Correlations of Food Web Metrics in Ecosystems	44
3.3.2	Ecological Metrics Outlier Exploration	47
3.3.3	Principle Component Analysis of Food Web Metrics	57
3.3.4	Cluster Analysis of Food Web Metrics	63
3.4	Discussion of PCA and Cluster Analysis	65
3.5	In Closing	68
 CHAPTER 4. The Application of Detrital Actors In Engineered Systems 70		
4.1	Research Tasks and Goals	70
4.2	Background & Motivation: The Decomposer Functional Role	70
4.3	Methods: From Theory to Implementation	72
4.3.1	Characterization and Classification of Common Waste Streams	73
4.3.2	Expansion of the Waste Stream Characterization and Classification Schema	76
4.4	Results and Discussion: A Database of Engineered Systems That Mimic Nature's Decomposer Functional Role	83
4.4.1	Feasibility Considerations	87
4.4.2	Broader Discussion of Results Using Waste Stream Matching to the Fields of Industrial Ecology and Circular Economy	90
4.5	Summary and Conclusions	92
 CHAPTER 5. A Generalized ENA Modeling Methodology and Its Application to Engineered Systems 94		
5.1	Research Tasks and Goals to be Addressed	95
5.2	Background	96
5.3	Generalized Model Formulation for Engineered Systems	98
5.3.1	Generalized System Component Model	98
5.3.2	Generalized ENA Modeling Methodology (ENAMM)	100
5.4	Case Study 1 – Automobile Manufacturing	108
Step 1 of General ENA Modeling Methodology (ENAMM) from Figure 19 – Identify System Boundaries		108
5.4.1	Assumptions in the Automotive “Ecosystem”	111
5.4.2	Initial Structural Development	113
5.4.3	Water Network	114
5.4.4	Material Network	121
5.4.5	Energy Network	125

5.4.6	Structural Combination of Water, Material, and Energy Networks	133
5.5	Case Study 2 – Carpet Manufacturing Model	137
5.5.1	Multi-Objective Optimization for Economic, Environmental, and ENA	142
5.5.2	Results and Discussion – Carpet Manufacturing Model Case Study	146
5.5.3	Conclusions	154
5.6	Conclusions	155
CHAPTER 6.	Bioaugmentation of a Steel Water Network Using Constructed Wetlands and Pyrolysis Modeling	157
6.1	Research Questions to be Addressed	158
6.2	Background	158
6.2.1	Steel Manufacturing Water Network: A Production Process with High Resource Consumption and Emissions	167
6.2.2	Biological Augmentation as a Possible Solution	168
6.3	Materials and Methods	170
6.3.1	Integration of Wetlands into the Water Network	170
6.3.2	Plant Species Selection	172
6.4	Pyrolysis as an End Use of Plants After Growing Period	178
6.5	Results and Discussion	180
6.5.1	Integration of Wetlands into the Water Network	180
6.5.2	End Use of Plants After Growing Period	185
6.5.3	Effect on Overall Material Structure by Employing the Wetland System	187
6.5.4	Cost Analysis of Employing the Wetland System	192
6.6	In Closing: Water, Energy, and Cost Savings with Biological Augmentation: A Possible Sustainable Framework	196
CHAPTER 7.	Summary and Future Work	199
7.1	Summary	199
7.2	Contributions	202
7.2.1	Uncovering the Fundamental Differences in Structural and Flow-Based Configurations in Ecosystems as Compared to Engineered Systems	202
7.2.2	A Quantifiable and Adaptable Design Framework for Performing ENA Analysis in Engineered Systems	203
7.3	Limitations	204
7.4	Future Work	205
7.4.1	Database Expansion	205
7.4.2	Refinement of Generalized ENA Modeling Methodology (ENAMM)	207
7.4.3	ENA Tool	208
7.5	In Closing	210
APPENDIX A.	Ecosystem Extraction	212
A.1	MATLAB Subroutine	212
A.2	Ecosystems	214
APPENDIX B.	Full Database of Biological Technological and Hybrid Solutions	223
B.1	Database	223

APPENDIX C. Case Studies Supplemental Information	225
C.1 Model Script Development	225
C.2 Data Pre-Processing	227
C.2 MATLAB Code	228
C.2 Automotive Case Study Network Structures	291
 APPENDIX D. Steel Water Network	 300
D.1 Steel Water Network	300
D.2 Universal Parameter Calculation	302
D.3 Initial Parameters for Pyrolysis Model	304
D.3 Pyrolysis Model Results	306
D.4 ENA Model Networks	308
 References	 313

LIST OF TABLES

Table 1	Nomenclature and Symbols Used in the Calculation of Network Indices	29
Table 2	Network Index Codes and Formulas.	30
Table 3	Description of ENA Measures	33
Table 4	Potential Outliers of the 100 Ecosystems Multivariate Analysis	49
Table 5	PCA Cumulative Percent of Variance Explained	58
Table 6	Cluster Summary	64
Table 7	Cluster Members	65
Table 8	NAICS Industrial Codes	74
Table 9	Waste Stream Categorization and Classification Matching Using the NAICS standard	74
Table 10	Relevant Information for Parametric Equation from	82
Table 11	Snapshot of Structural Connections Database that Includes Biological, Technological, and Hybrid Solutions to Waste Streams.	85
Table 12	Snapshot Flow Connections Database that Includes Biological, Technological, and Hybrid Solutions to Waste Streams	86
Table 13	Component Breakdown of Consumption and Production	111
Table 14	Structural Ecological Metrics Linkage Density and Connectance for Water Network Scenario Exploration	120
Table 15	Material Scenario Structural Ecological Metrics Results	125
Table 16	Energy Structural Ecological Network Results for the Automotive Manufacturing Ecosystem	133
Table 17	Structural Ecological Metrics Results for Combined Material, Water, and Energy Networks Meta-Model	135

Table 18	Minimum Flow Constraints to Counties	139
Table 19	Optimization Algorithms Adopted by	140
Table 20	The Weighted Sum Multi-Objective Optimization Method with Scalar Transformations	143
Table 21	Objective Function results and ecological metric values from original carpet study as compared to the current study. Original metric values found in (Astrid Layton, 2016) and (Reap, 2009).	147
Table 22	Steel Water, Material, and Energy Flows in the Modeled Steel Manufacturing Network.	163
Table 23	ENA Metrics Results for the Current Steel Material and Water Network	165
Table 24	Plant species selection with sources from literature. The data source row lists the publication source from literature. The data source notes row describes location/scenario of the data used in this study found within these sources	173
Table 25	ENA structure and flow results	182
Table 26	Material and Water Flows of a Steel Industry with Constructed Wetlands and Pyrolysis	189
Table 27	ENA Model Results of Original Steel Material and Flow Meta-Model with Results from the Model with Constructed Wetlands and Pyrolysis	191
Table 28	100 Ecosystem Dataset	215
Table 29	Database of Biological, Technological, and Hybrid Solutions	224
Table 30	Current Water Network of Automotive Case Study	291
Table 31	Automotive Water Network with Rainwater Capture	292
Table 32	Automotive Water Network with Graywater Systems	292
Table 33	Automotive Water Network with All Scenarios and Community Integration	293
Table 34	Automotive Material Network	293

Table 35	Automotive Material Network with Recycling	294
Table 36	Automotive Material Network with Closed-Loop Recycling	295
Table 37	Current Automotive Energy Network	295
Table 38	Automotive Energy Network with Hydrogen Generation	295
Table 39	Automotive Energy Network with Photovoltaics Expansion	296
Table 40	Automotive Energy Network with Microgrid Configuration	297
Table 41	Automotive Energy Network with All Energy Scenarios	297
Table 42	Current Automotive Material, Water, and Energy Meta-Model	298
Table 43	Best Case Automotive Meta-Model	299
Table 44	Universal Parameter Calculation from Farzi, 2017	302
Table 45	Universal Parameter Calculation for Rosema, 2016	303
Table 46	Universal Parameter Calculation for Zhao, 2005	303
Table 47	Numerical Integration Initial Conditions	304
Table 48	Parameter Estimation for Pyrolysis Model (95% Confidence Interval)	305
Table 49	Fitted Curve Statistics for Pyrolysis Model (95% Confidence Interval)	305
Table 50	Pyrolysis Model Results and Confidence Error Bands Results	306
Table 51	Wetlands and Pyrolysis Calculations for Chloride Removal	307
Table 52	Uptake Calculation for Different Plant Species	308
Table 53	Steel Water Network Without Wetlands	309
Table 54	Steel Water Network with Wetlands	310

Table 55	Current Chinese Steel Industry Material, Water, and Energy Meta-Model	311
Table 56	Best Case Chinese Material, Water, Energy Steel Manufacturing Meta-Model	312

LIST OF FIGURES

Figure 1	Circular Economy Principles. Adapted from the Ellen MacArthur Foundation (The Ellen MacArthur Foundation, 2012).	2
Figure 2	Growth in Population and Atmospheric Greenhouse Emissions Since the Beginning of the Industrial Revolution. <u>Top Left:</u> The Global Population Growth (Klein Goldewijk, Beusen, & Janssen, 2010; Kremer, 1993; United Nations, 2019). <u>Bottom Left:</u> The Global Atmospheric Composition of Carbon Dioxide (Bernhard Bereiter et al., 2015). <u>Top Right:</u> The Global Atmospheric Composition of Nitrous Dioxide ((EEA), 2018). <u>Bottom Right:</u> The Global Atmospheric Composition of Methane (European Environment Agency (EEA) & (NOAA), 2019).	21
Figure 3	Ecosystem Functional Roles	24
Figure 4	Food Web Interpretation of Ecosystem	25
Figure 5	Graph Theory Origins – Euler’s Bridges	27
Figure 6	Pearson Product Moment Correlations Amongst Food Web Metrics	46
Figure 7	Outlier Detection Using Mahalanobis Distance	48
Figure 8	Correlation Plot After Exclusion of Outliers	54
Figure 9	Malahanobis Distance After Exclusion of Outliers	55
Figure 10	Correlation Analysis Without Outlier Exclusion	56
Figure 11	Histogram and Simple Statistics of Key Ecological Metrics	57
Figure 12	Loading Plot of Metric Impact Among Components	59
Figure 13	Biplot of Metric Loading Among the First Two Components	60
Figure 14	Scree Plot of Eigenvalue per Number of Components	61
Figure 15	Partial Contribution of Variables in PCA Analysis	63

Figure 16	Steps to Generate Biological, Technological, or Hybrid Decomposers	77
Figure 17	General Feasibility Considerations with Example	88
Figure 18	System Component Definition	99
Figure 19	Generalized ENA Modeling	101
Figure 20	Automobile Manufacturing Plant	109
Figure 21	High-level Energy and Material Systems Model	110
Figure 22	Original Water Network Structure. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina, Bodini, Bondavalli, & Lundbers, 2005).	115
Figure 23	Rainwater Capture Water Network Scenario Exploration of the Automotive Manufacturing Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).	116
Figure 24	Graywater Systems Water Network Scenario Exploration of the Automotive Manufacturing Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).	118
Figure 25	Combined Rainwater Capture and Graywater Utilization with Community Oriented Expansions Water Network Scenario Exploration of the Automotive Manufacturing Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node	119

can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).

- | | | |
|-----------|---|-----|
| Figure 26 | Original Material Network in the Automotive Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005). | 122 |
| Figure 27 | Increased Recycling Material Scenario Exploration within the Automotive Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005). | 123 |
| Figure 28 | Closed-loop Recycling Material Scenario Exploration within the Automotive Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005). | 124 |
| Figure 29 | Original Energy Network in the Automotive Manufacturing Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005). | 126 |
| Figure 30 | Hydrogen Generation Energy Scenario Exploration in the Automotive Manufacturing Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005). | 127 |

Figure 31	The Implementation of a Microgrid with the Surrounding Community in Energy Network Scenario Exploration of the Automotive Manufacturing Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).	129
Figure 32	Expanded Solar Energy Generation Capacity Scenario Exploration in the Automotive Manufacturing Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).	131
Figure 33	Combined "Best-Case" Structural Energy Network of the Automotive Manufacturing Ecosystem to Include an Expanded Solar Generation Capacity, Hydrogen Generation and Fueling, and Microgrid Capabilities. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).	132
Figure 34	Original Combined Network Structure that Includes Materials, Water, and Energy Systems. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).	134
Figure 35	Best Combined Network Structure that Includes Materials, Water, and Energy Systems. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node	135

and the path will cycle back to the original node (Allesina et al., 2005).

Figure 36	Carpet Material Recycling Network Model Developed by (Reap, 2009) and Adapted by	138
Figure 37	Pareto plot comparing two objectives (FCI and Total System Cost) with the objective function value.	149
Figure 38	Linear regression of shows the FCI on the x-axis and the Total System Cost on the y-axis	150
Figure 39	Residuals of linear fitted model shows the FCI on the x-axis and the total system costs on the y-axis	151
Figure 40	Linear fitted model of FCI vs the objective function value	152
Figure 41	Residuals plot of the linear model of FCI vs objective function value	153
Figure 42	Life Cycle Flows of Steel	160
Figure 43	Current Steel Water and Material Structure	162
Figure 44	Illustration of using a combined constructed wetlands and pyrolysis process in basic oxygen furnace steel making	170
Figure 45	The simplified flows of water throughout a steel manufacturing park. The nodes (brown) represent major elements of the steel park. The weighted edges between these nodes are representative of flow magnitude ranging from $0.05 \text{ m}^3 \text{ hr}^{-1}$ to $43650 \text{ m}^3 \text{ hr}^{-1}$.	171
Figure 46	Chloride accumulation rate ($\text{g d}^{-1} \text{ m}^{-2}$) of several plant species from various sources in literature. The five green bars represent halophytic plants, where the two brown bars are non-halophytic plant species. The vertical bars represent the mean value \pm the propagated standard error from the respective studies.	177
Figure 47	The pyrolysis reaction kinetics used in this study. The modeled change of solids over time during pyrolysis is the sum of biomass, intermediate, and char.	179
Figure 48	The simplified flows of water in a steel manufacturing park to the addition of constructed wetlands. The nodes in brown represent major elements in the steel park, while the weighted edges between these nodes are representative of flow magnitude ranging from $0.13 \text{ m}^3 \text{ hr}^{-1}$ to $43650 \text{ m}^3 \text{ hr}^{-1}$. The green node and	181

edges shown in this figure represent the flows that differ from the original steel manufacturing network shown in Figure 45.

Figure 49	Flowrate changes from the original model to the model incorporating the wetlands. The green points represent flows originating from freshwater sources, where the brown dots are flows originating from other elements in the steel manufacturing water network. This figure excludes flows greater than $800 \text{ m}^3 \text{ hr}^{-1}$ and flows that differ structurally.	184
Figure 50	Pyrolysis model of <i>Salicornia</i> under a constant heating rate of 5 K min^{-1} and starting temperature of 298 K .	186
Figure 51	Steel Industry Material and Water Flow-Based Model with Constructed Wetlands and Pyrolysis Process	188
Figure 52	ENA Tool with Model Setup	209
Figure 53	ENA Tool Showing Modeled System and Connections	210
Figure 54	Unsimplified Steel Water Network	301

LIST OF SYMBOLS AND ABBREVIATIONS

AC	Extent of Development
AMI	Average Mutual Information
BFG	Blast Furnace Gas
BID	Bio-Inspired Design
BOF	Basic Oxygen Furnace
BOFG	Basic Oxygen Furnace Gas
BREEAM	Building Research Establishment Environmental Assessment Methodology
C	Connectance
CDQ	Coke Dry Quenching
CE	Circular Economy
COG	Coke Oven Gas
COP	Coefficient of Performance
CSI	Chinese Steel Industry
CW	Constructed Wetlands
DGNB	German Sustainable Council System
DOE	Department of Energy
EIP	Eco-Industrial Park
ENA	Ecological Network Analysis
ENAMM	ENA Modeling Methodology
EPA	Environmental Protection Agency
FCI	Finn Cycling Index
GRBS	Green Building Rating System

HSSF	Horizontal Subsurface Flow
IE	Industrial Ecology
ISO	International Organization for Standardization
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LD	Linkage Density
LEED	Leadership in Energy and Environmental Design
MFA	Material Flow Analysis
NAICS	North American Industry Classification System
NASA	National Aeronautics and Space Administration
NOAA	National Oceanic and Atmospheric Administration
NREL	National Renewable Energy Lab
O&M	Operations and Maintenance
ORNL	Oak Ridge National Lab
PCA	Principal Component Analysis
PV	Photovoltaics
PVC	Poly Vinyl Chloride
ROC	Reverse Osmosis Concentrate
ROI	Return on Investment
STEM	Science, Technology, Engineering, Mathematics
TCE	Tons of Coal Equivalent
TEA	Techno-Economic Analysis
TRT	Top gas pressure Recovery Turbine
UCL	Upper Control Limit

WWT Wastewater Treatment

SUMMARY

The current industrial production model meets population-driven demand in an unsustainable manner, generating vast amounts of environmental pollution and material waste that threatens global economic stability and changes Earth's climate. It is understood that a key element to developing a more sustainable manufacturing model is through efficient and effective resource utilization, a goal that mature biological systems achieve through the implementation of intricate decomposing networks. These decomposing networks are essential for a healthy and mature ecosystem because these organisms cycle nutrients and energy that would otherwise be lost and reintroduce them back into the ecosystem.

These fundamental qualities of increased connectivity and cycling behavior can be quantified in ecosystems through the use of Ecological Network Analysis (ENA). In this dissertation, we used ENA and multivariate statistics to analyze over 100 ecosystems and found several fundamental metrics for explaining ecosystem functionality in a combined principal component analysis and cluster analysis. We used these metrics to introduce a database of classified and categorized engineered “decomposers” as interventions to waste streams in the industrial realm akin to those found in natural ecosystems. The goal in the application of these “decomposers” is to create both denser connections and increased waste-stream cycling in engineered systems.

However, in the application of these “decomposers,” we found there currently is no generalized modeling methodology for applying ENA to engineered systems design today. Thus, much of the ENA of engineered systems is ad hoc and segmented to analysis alone.

Further, ENA’s application to engineered systems is isolated to those academics that grasp the intersection of the subjects of mathematics, engineering, and biology. As such, there is a need to expand ENA’s application so the remainder of academia and the design community can leverage its benefits.

Therefore, we introduce a way to model, quantify, and improve the performance of engineered systems using ENA in a generalized manner. We develop a mathematical model to describe engineered systems components and combine this model with an 8-step quantitative methodological approach called ENAMM. ENAMM includes rules, goals, assumptions, and suggestions for ENA’s application to engineered systems. At its core, ENAMM leverages the ENA metric values set by our multivariate analysis of 100 ecosystems as indicators of a healthy balance in a network's structure and flow configuration in ENA’s application to engineered systems design. An iterative design approach with our “decomposer” database and ENA attempts to close the material and energetic performance gap found between natural ecosystems and engineered systems. Finally, we then subject our ENAMM to testing and validation through its application to three case studies.

The first case study is the structural analysis of an automobile manufacturing facility. This case study investigates the essential initial steps of the proposed ENAMM – the underlying assumptions one might propose, the identification and establishment of system boundaries, and the identification of the correct level of coarseness when breaking the high-level systems down to the components inside system boundaries. This study also shows the formation of a meta-model, by combining water, material, and energy

components of an engineered system and calculating the progression of ENA values from the initial structure model to the final model.

The second case study explores the latter stages of the proposed ENAMM with an example of a carpet manufacturing recycling network. This study's objective is to demonstrate the flow and feasibility analysis of an engineered system using ENA. The feasibility analysis included the optimization of the economic effects of the assignment of flows in the network, the consideration of environmental costs through pollution generation, and achieving set target goals for ENA metrics in the final model.

Finally, we present a third and final case study of steel manufacturing that includes all steps of the proposed ENAMM. This case study demonstrates how readily available technology can address the sustainability challenges within the steel industry by looking to nature to provide both services and insight into the organization of these systems. This case study first develops a system-wide material and water model. Through a Mass Flow Analysis (MFA), the potential behind incorporating technological and biological interventions in the steel manufacturing water network is uncovered, and thus the study shifts to exploring interventions to waste in the water network. Using the ENAMM resulted in increased material and energy efficiency in an integrated steel manufacturing facility through the optimized bioaugmentation of constructed wetlands for water treatment and pyrolysis for energy generation. The feasibility results suggest a 1.65 to 4.03-year payback period and is a clear win for a more sustainable steel industry. This case study provided confirmation of the ENAMM applied to a top-to-bottom analysis of an engineered system, and the results demonstrate a considerable improvement of costs in addition to the traditional sustainable benefits of increased material and energy efficiencies.

We believe ENAMM provides a fundamental contribution to science and engineering by increasing both the depth of where ENA could be applied and by whom. In this dissertation, ENAMM has shown to fortify and expand the established underlying principles of closed-loop cycling in the growing fields of Industrial Ecology and Circular Economy. In addition, the case studies ENAMM is applied to highlight the fundamental differences of structural and material flow-based configurations in engineered systems as compared to those found in natural systems. We know from our analysis of 100 ecosystems that natural systems focus on optimizing the use of natural resources to live within the material constraints of their surroundings. Alternatively, our case studies of engineered systems demonstrate a focus on an efficient linear structure.

Our research has shown that adopting a more holistic approach to the design of engineered systems, such as using natural ecosystems as a template for sustainable systems design, is one way to achieve a more sustainable industrial production model. By providing a quantitative means and an established methodology for iteratively assessing engineered systems to achieve established design targets, it is believed that this dissertation provides a step towards changing the currently subjective (and often limited) practice of sustainable systems design. Our ENAMM looks to commonly regarded waste streams as potential resources and brings sustainability to the forefront of discussion in the design process, instead of an afterthought. The changes in approaching engineered systems design presented in this dissertation offer a potential step towards what is needed to face the current climate crisis and sustain the growing world population while still meeting industrial demand.

CHAPTER 1. INTRODUCTION

1.1 Motivation

Life has existed on this planet for nearly 3.8 billion years and has evolved into the sustainable configuration that modern humans have occupied for only the past 200,000 years (Mojzsis et al., 1996; Stringer, 1990; United Nations, 2019). Human practices have pushed the planet into a new geological era in this short timeframe, the Anthropocene, marked by land-use changes, deforestation, and fossil fuel burning (Crutzen, 2006; Lewis & Maslin, 2015). The world now faces extraordinary environmental challenges due to these practices and is in desperate need of improved methodology and solutions that will allow for sustainable future inhabitation (Preston, 1996).

Industrial Ecology (IE) is a well-developed field of inquiry that uses high-level principles from ecology to guide the design of human industrial processes away from linear configurations towards more closed-loop systems. Traditional applications include Industrial Symbiosis, Urban Metabolism, Material Flow Analysis (MFA), and Life Cycle Analysis (LCA) (T. E. Graedel & Allenby, 1995). The principles behind IE form the basis for the concept of Circular Economy (CE). CE is an economic system originating in the late 20th century that is geared towards eliminating wastes through reuse, recycle, repair, refurbishment, remanufacturing, and recycling (Erkman, 1997; Frosch, 1992; Ghisellini, Cialani, & Ulgiati, 2016). Its principles are demonstrated below in Figure 1 (The Ellen MacArthur Foundation, 2012).

OUTLINE OF A CIRCULAR ECONOMY

PRINCIPLE

1

Preserve and enhance natural capital by controlling finite stocks and balancing renewable resource flows
ReSOLVE levers: regenerate, virtualise, exchange

PRINCIPLE

2

Optimise resource yields by circulating products, components and materials in use at the highest utility at all times in both technical and biological cycles
ReSOLVE levers: regenerate, share, optimise, loop

PRINCIPLE

3

Foster system effectiveness by revealing and designing out negative externalities
All ReSOLVE levers

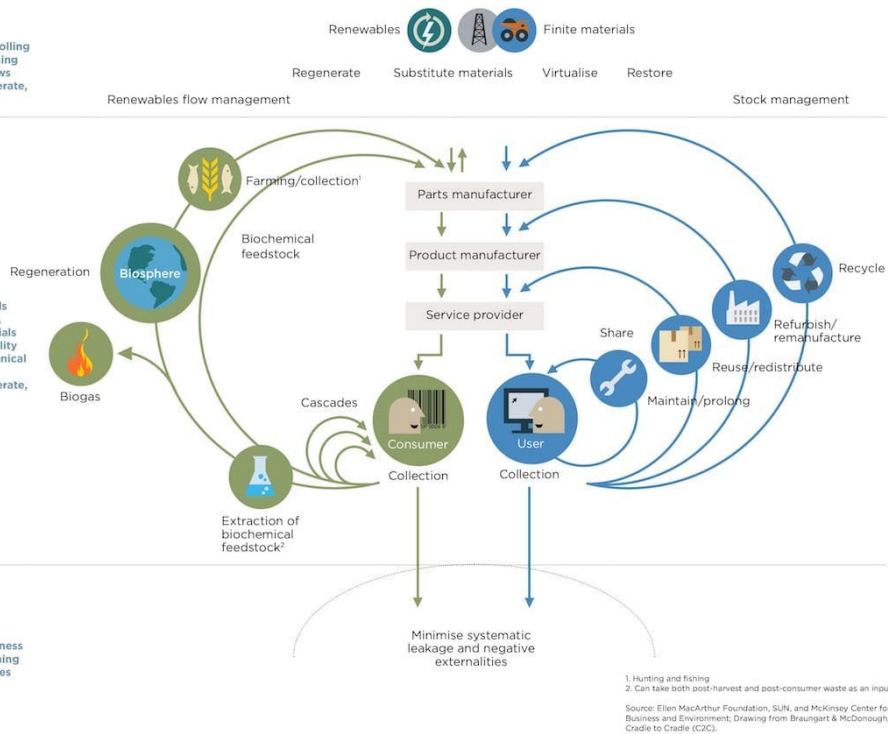


Figure 1. Circular Economy Principles. Adapted from the Ellen MacArthur Foundation (The Ellen MacArthur Foundation, 2012).

While the shift to this more circular economic and material structure has started through climate-driven worldwide agreements, the design community needs improved frameworks and impact-driven tools to assist in the transition to a more sustainable world (Bodansky, 2016; United Nations, 1998).

The design stage of engineered systems offers the greatest impact potential in the sustainable outcome of the design (Bras & Woodruff, 1999; Thomas E. Graedel, Comrie, & Sekutowski, 1995). Realizing this, engineering design in this age of connectivity is increasingly complex with seemingly endless linkages between commerce, communication, and transportation. Sustainable designs must balance the triple bottom line

of the environmental, social, and economic shareholders from conception. They must also include the factors of CE in addition to safety, security, design for manufacturing, environmental impact, serviceability, and impact on future generations (Anastas & Zimmerman, 2003). There is a host of general principles from varying sources used to guide the engineering community's ideation phase today, for example: (1) Design consistent with ecological principles; (2) Design for site-specific context; (3) Maintain independence of design functional requirements; (4) Design for efficiency in energy and information; (5) Acknowledge the purpose that motivates design (Bergen, Bolton, & L. Fridley, 2001; Mitsch & Jørgensen, 2004).

The qualitative frameworks embodied by these principles are subjective in nature. In our discussions with partners in private industry they revealed that many planners and large-scale development firms have their own internal documentation seeking to align impact objectives with environmental policies and industry standards while catering to client preferences on a case-by-case basis (Foran, 2019). Although these sustainable design methods can reduce project-specific impacts, the common frameworks are either: (1) entirely subjective in nature – requiring the designer to make decisions based on loosely-structured sustainability objectives and lacking a quantitative methodology – or (2) only guide decision at the unit-process level and neglect the multiple interactions and interdependencies of the overall system. As such, designers need a quantitative benchmark and sustainable design methodology with which they can mitigate environmental burdens (Dalibi et al., 2017; Hankinson & Breytace, 2012; Hes, 2005; Israel O., Andrew, Paul, & Pamela, 2017). William Thompson (Lord Kelvin) once said in a lecture on May 3rd, 1883 (Stellman & International Labour, 1998):

“I often say that when you can measure what you are speaking about, and express it in numbers, you know something about it; but when you cannot express it in numbers, your knowledge is of a meagre and unsatisfactory kind; it may be the beginning of knowledge, but you have scarcely, in your thoughts, advanced to the stage of science, whatever the matter may be.” -Lord Kelvin

Without such quantitative benchmarking tools, designers are currently unable to model, monitor, and evaluate how a system might perform at a macro level over time. The ability to quantifiably measure a sustainable design allows for management of the results, and managed results allow for improvement.

1.2 Ecological Systems Inspiration and Integration into Designed Systems

Experts in the field of IE equate industrial activity today to opportunistic, immature natural systems, which are those that have developed quickly in the presence of abundant resources (Allenby & Cooper, 1994). The organisms within these systems utilize a rapid growth strategy, squandering resources by maximizing material throughput (Enger & Smith, 2008). Similar to the unregulated growth demonstrated by immature natural systems, industrial activity has grown in size since the industrial revolution to meet population-driven increased demand at an extreme pace that focuses on output regardless of material wastes. By contrast, mature ecological systems have evolved to live within the resource constraints of their environment. These systems embody sustainability through material efficiency, demonstrating intricate decomposing and cycling networks (Carrer & Opitz, 1999). The majority of organisms that comprise mature ecosystems optimize, rather than maximizing production (Schidlowski, 1988).

Ecologists apply fundamentals of graph and information theory to derive metrics that measure ecosystem characteristics and performance in a field called Ecological Network Analysis (ENA) (B. D. Fath & Halnes, 2007; J. T. Finn, 1976; R. E. Ulanowicz, 1983; Robert E Ulanowicz, 2000; Robert E. Ulanowicz, Holt, & Barfield, 2014). Some scientists have adapted this approach to compare the structural design and performance of engineered systems to that found in natural ecosystems (B. D. Fath & Halnes, 2007; Brian D. Fath, Scharler, Ulanowicz, & Hannon, 2007; Astrid Layton, Bras, & Weissburg, 2017; A. Layton, Reap, Bras, & Weissburg, 2012; Stephen M. Malone, Weissburg, & Bras, 2018; Robert E. Ulanowicz et al., 2014). The translation of functional roles, structural connectivity, and flow-based configurations found within mature natural ecosystems into engineered systems is accomplished by abstracting basic functions that exist within both industry and nature, such as the consumption of energy and materials, transforming materials and energy into products, and breaking down products to make them re-available (Allenby & Cooper, 1994; Brian D. Fath & Patten, 1999; Brian D. Fath et al., 2007).

Using this translational approach to describe and model engineered systems from an ecological perspective, scientists show strong disparities between human and natural systems (Levine, 2003). For instance, engineered systems are characterized by a limited number of primary consumers (herbivores in natural ecosystems) and abundance of dependent consumers (carnivores in natural ecosystems), while the decomposer functional role found in nearly all natural systems is often lacking or absent altogether (Astrid Layton et al., 2017). This decomposer functional role in natural systems, comprised of detrital feeders named detritivores (e.g. earthworms, slugs, millipedes, etc.) and decomposers (e.g. fungi), is vital to natural ecosystems in that they are nature's core recycling components. This material cycling

deficiency in engineered systems has led to dependence on virgin resources, and it has subjected industrial systems to supply chain vulnerability as well as contributing to the global environmental crisis through excess waste generation. By contrast, natural systems that possess these detrital feedback loops exhibit improved performance metrics in these domains, such as structural stability and efficiency (Haines, Fath, & Liljenström, 2007). These types of metrics are highly sought after in engineered systems. Thus, improvements that originate from the decomposer functional role and its interactions found in natural systems must be leveraged when translating ecosystem structure and flow-based properties to sustainable industrial systems, as these indicators are some of the major determinants of longevity and profitability amongst corporate industries today (Nitin, Joyce, & Robinson, 2003).

1.3 The Mission and Potential Impacts of This Research to Address Current Knowledge Gaps

There is a current need in the design community by professionals and academics alike for an adaptable and quantitative methodology to assess the sustainable design of engineered systems. This methodology, or tools to apply this methodology, do not yet exist. The research in this dissertation seeks to address this need by building on the foundation established by previous IE, CE, and Bio-Inspired Design (BID) researchers (Guidry, 2008; Astrid Layton, 2016; Morris, 2020; Reap, 2009).

This research leverages biologically inspired design methods to analyze and measure the performance of engineered systems. This performance is measured in this dissertation in several traditional manners, such as cost and/or environmental impact due to emissions or energy and/or material consumption. We also consider ENA metrics as an untraditional

measure of performance. However, it is not currently understood which metric(s) in ENA (over twenty-four common metrics and countless others) best describe ecosystem performance or functionality. Therefore, this thesis first statistically analyzes 100 mature natural ecosystems to better understand which of these ENA metric(s) are fundamental, pare down the metrics that are highly correlated, and to establish target values to compare performance from engineered systems.

We then seek improve these fundamental ecological metrics when applied to engineered systems. This is accomplished by mimicking the densely connected and cyclic nature of this decomposer role by collecting a database of “decomposing” engineered systems that may be operationalized for use by academic researchers or industry professionals in the design phase. Such a database of these decomposing engineered systems does not yet exist, and the hope is that by establishing an initial database with the expectation for it to grow, we can spur activity from academic researchers or industry professionals to contribute or create their own.

In order to provide a substantiated, actionable roadmap for designers to follow, this thesis then develops a generalized mathematical modeling methodology for Ecological Network Analysis’ use in engineered systems. Such a methodology does not yet exist but is needed to guide and educate industry professionals or academics in the field of IE wishing to use Ecological Network Analysis to analyze engineered systems. The fundamental ENA metrics then assist in augmenting the structural and flow-based configurations in this mathematically modeled engineered system through the introduction of waste-stream targeted technological, biological, or hybrid “decomposing” engineered systems. The augmented engineered system is then optimized for flow-based ecological metrics and/or cost to address

the material or energy performance gaps between engineered and natural systems. Finally, subsequent testing and validation of this methodological approach on varying engineered systems ensure flexibility in application across the design landscape.

This research addresses a need in the design community for a systematic methodology and application in the proper identification and utilization of these essential decomposing systems that may then be adapted to any modeled system. We also further the use of the ENA method in the field of Industrial Ecology and continue to test its effectiveness in sustainable network design by adapting modeling and analysis into a design tool.

1.4 Overall Research Question

Does an ecologically inspired metric-based approach to the conceptual design of engineered systems provide structural or flow-based translative insight to the configurations that lead to sustainability gains as measured by reduced natural resource consumption and material waste?

1.5 Research Goals

1.5.1 Apply statistical methods to identify the key ENA metrics of ecological systems that most succinctly describe ecosystem performance.

It is not currently understood which of the over twenty-four common ENA metrics best encapsulate the emergent properties of ecosystem performance. This understanding will allow for a more direct assessment of how ecosystem configurations differ from engineered systems. If achieved, this more thorough understanding of these metrics would allow for a more direct approach of the ENA applied to engineered

systems may foster more widespread adoption from industry professionals and academics alike.

1.5.2 Create a repository of biological, technological, or hybrid interventions that mimic the decomposer functional role in natural ecosystems

Current research shows that engineered systems do not achieve the same levels of energetic and material performance of natural ecosystems. To address this performance gap and to accelerate ENA's adoption in industry, we introduce a repository of biological, technological, and hybrid interventions that can increase the connections and cycling of an engineered system. By classifying and characterizing these interventions, this repository will allow for easy and intuitive matching of waste streams in engineered systems to better mimic the structural configurations of those found in natural ecosystems.

1.5.3 Create and apply a generalized ENA-based design methodology for the model-based design of engineered systems

To date, there is no established methodology for applying ENA to the model-based design of engineered systems. Research has shown that novices show distinct differences and struggle with design-by-analogy execution as compared to experts (Fu, Moreno, Yang, & Wood, 2014). Therefore, we believe the creation of such a methodology with help transfer key knowledge to novices and lead to faster adoption of ENA from practitioners and academics in the design of engineered systems.

1.6 Fundamental Research Contributions

This dissertation applies quantitative insight from nature to more sustainably design engineered systems. While rudimentary means to model engineered systems using ENA have been developed and applied in an academic setting, doing so requires substantial knowledge in both engineering and ecosystem dynamics for a user to make correct assumptions in performing an analysis. This dissertation provides a more robust methodological modeling and validation framework for applying ENA to engineered systems that is fundamentally rooted in the core principles and properties of natural ecosystems.

1.6.1 Uncovering the Fundamental Differences in Structural and Flow-Based Configurations in Ecosystems as Compared to Engineered Systems

The fundamental structural and material flow-based configurations differ between engineered and natural systems. Literature on engineered systems demonstrates a focus on an efficient linear structure, while natural systems alternatively optimize the use of natural resources to live within the material constraints of their surroundings. However, there is a lack of research today on how these directly compare while also considering the size and material throughput of these systems. This suggested approach using ENA uncovers insight as to the structural and material-based configurations that lead to material and energy efficiency.

1.6.2 Broadening Current Research in the Field of Industrial Ecology

This iterative design approach to engineered systems using ecosystem metrics fortifies and expands the underlying principles of closed loop cycling in the field of IE. In addition, this approach broadens the application of ENA, which is typically only used for the analysis of ecological systems and has yet to be implemented in the iterative conceptual design of engineered systems outside of academic realm.

1.6.3 A Quantifiable and Adaptable Design Framework for Performing ENA Analysis in Engineered Systems

A tested, validated, and quantitative ENA modeling methodology is needed to identify and address the material and energy efficiency shortcomings of engineered systems using readily available technological, biological, or hybrid solutions. This methodology should increase the performance of these engineered systems to that found in natural ecosystems. The author has not identified an existing methodology or toolkit in literature or industry today that utilizes this approach at design conception that is both quantifiable and adaptable. This contribution can inform and empower the design community at the most influential stage of the design cycle by allowing professionals to monitor, manage, and improve the suggested outcomes of their designs.

1.7 Research Tasks

We answer the proposed research question (RQ) and goals (RGs) by performing the following tasks (RTs):

RT1. Collect and compile case studies of human engineered and high-quality natural ecosystem data from industry and literature sources. This task contributes to the completion of research goal 1.5.1.

We are to gather 100 ecosystems of varying size and complexity from literature. These ecological systems should originate from validated databases established and managed by ecologists. These systems will be processed using best techniques (as defined by ecologists) to ensure a properly calibrated model. Next, these systems will be analyzed using ENA.

The engineered systems of this dissertation include case studies from across the industrial landscape and world. The first case study is of an automobile manufacturing plant in the state of South Carolina in the United States. The second case study is of a carpet manufacturing and recycling network in the state of Georgia in the United States. The final case study is of a steel manufacturing facility in Liaoning Province in northeast China. The data for all three engineered systems case studies originate from industry partners.

RT2. Perform a literature review of technological, biological, or hybrid interventions that address the material and energy shortcomings of human engineered systems to elevate the performance of these systems to those found in ecosystems. This task contributes to the completion of research goal 1.5.2.

A literature review will be performed of the technological, biological, and hybrid systems (e.g. constructed wetlands, cogeneration systems, or water treatment systems) that address the material and energy efficiency shortcomings of engineered systems. The incorporation of these interventions is expected to elevate the performance of engineered systems to those found in natural ecosystems. Technological systems are the conventional approach in engineering to address this performance gap, so the primary focus in this thesis is the incorporation of biological

and hybrid systems. These biological and hybrid systems should originate from high-quality literature sources such as Ecological Engineering, Journal of Cleaner Production, Environmental Science and Technology, and the Journal of Industrial Ecology. However, certain design criteria do not allow for the existence of natural or hybrid solutions (e.g. clean rooms, pharmaceutical plants, harsh environments, etc.), and thus technological solutions will also be investigated to a lesser degree as to address these needs.

RT3. Classify these technological, biological, or hybrid systems based on their physical characteristics, their domain of influence, and ranked by their environmental, social, economic limitations, and performance potential using high-level parametric equations. This task contributes to the completion of research goal 1.5.2.

We are to classify the technological, biological, or hybrid systems found in RT2 based on their physical characteristics, their inputs domain of influence (material, energy, water), their design-level treatment type and capacities, and ranked by their limitations (applicability in an engineering context considering environmental, social, and economic ramifications). The deliberate classification of these systems allows for sound solution recommendations when addressing the performance gaps of engineered systems when compared to ecological systems. The key to success in this research task is the determination of high-level design estimates for the biological, technological, or hybrid systems to guide the development of parametric equations that describe their treatment capacities and sizing (high and/or low values, averages, assumptions, and estimations of error when appropriate and available). These estimates are not meant to be reflective of absolute certainty, as the overall research goal exists at a much higher level in the design process.

RT4. Analyze case studies of human engineered systems and natural ecosystems using ecological metrics to determine a baseline of comparison on how both systems perform. This task contributes to the completion of 1.5.1.

We analyze the case studies of human engineered systems and natural ecosystems using ENA metrics to determine a baseline of comparison on how both systems perform. The focus of this dissertation lies in addressing the performance gap left in engineered systems by not having key structural or flow-based configurations - such as adequate cycling components or strongly connected components - that are present in mature natural ecosystems. As such, this task includes scenario exploration of incorporating the biological, technological, and hybrid solutions from RT2 and RT3 or elsewhere in our case studies' model to increase the ENA metrics and close the performance gap when compared to natural ecosystems.

RT5. Statistically analyze the structural and flow-based variations of natural versus industrial systems to robustly identify any material and energy efficiency shortcomings. This task contributes to the completion of research goal 1.5.1.

As modeled systems grow in complexity, the identification of key cycling components in that system becomes increasingly difficult. This task is to analyze the structural and flow-based variations of natural versus industrial systems to robustly identify any material and energy efficiency shortcomings by using natural ecosystems as the baseline.

Engineered systems, especially industrial systems, are typically linear production processes that allow for easy identification of high material or energy (i.e. strongly linked) pathways. Due to the network construction and interactions found in ecosystem food webs, this identification is not as straightforward. To be able to effectively translate ecosystem principles and

properties to engineered systems, a method to identify and match the specific variations of network construction and flow distributions must be utilized.

There are several mathematical and algorithmic methods in literature and industry that identify specific variations in network topology (Bellingeri & Bodini, 2015; Pavlopoulos et al., 2011; Shi, Bonner, Adamic, & Gilbert, 2009). Some of these variations of network structure or flow distributions include thermodynamic pathways analysis using spanning tree algorithms, statistical connectedness or centrality in graphs, multivariate statistical methods, or estimating the importance of edges in a graph through a numerical weighting algorithm such as Google's PageRank. One, or a combination of these approaches, will allow for a robust and generalized scheme to identify existing (and the absence of) specific cycling components when mathematically modeled in both natural and engineered systems.

RT6. Develop a means to model engineered systems case studies in a generalized manner using ENA. This task contributes to the completion of research goal 1.5.3.

This task is to develop a means to model both ecosystems and engineered systems in a generalized manner using ENA. This generalized modeling approach must be able to incorporate the technological, natural, and hybrid interventions from RT2 and RT3 to augment and optimize the model. This task involves the creation of a methodology that designers may follow at the concept phase of human engineered systems design and utilize the collection found in RT3 to improve their designs.

RT7. Validate methodology by analysis of case studies of varying scales and complexities. This task contributes to the completion of research goal 1.5.3.

This task is to validate the methodology in RT6 by analysis of case studies of varying scales and complexities. The design of engineered systems is multifaceted, with many different stakeholders with competing interests. By developing an iterative process model tested with real-world designs at varying levels of complexity, location, scale, and types of stakeholders, we can ensure a useful, flexible, comprehensive, and robust design recommendation as a result.

1.8 Research Limitations and Assumptions

The primary assumption of the proposed research is mature ecosystems are inherently sustainable and that by mimicking their behavior, the proposed design solutions inspired by the translation of the ecosystems' functional properties to engineered systems will result in material and/or energy efficiency improvement. As such, this work acknowledges that the ecosystem food web datasets gathered by field ecologists have inherent human and measuring error. The author of this work is not an Ecologist and thus the ecosystem data in this work uses the data and error as presented in the respective studies.

Similarly, the engineered systems of the proposed work also have errors associated with the measuring of material or energetic flows in the systems and this work will again utilize the data as provided by industry or literature. In addition to this, the resolution of the engineered systems may limit the proposed analysis and research findings of this work.

The final limitation of this research lies with the relatively small sample size of engineered and natural ecosystems in relation to the amount of these systems in the world. Inevitably, new data or unforeseen variations of systems configuration, quantification, and/or scaling will uncover the need to revisit the methodology proposed in this research. Realizing this, this work includes

flexibility in all aspects of the methodology from inception to improve the likelihood of its successful application in both academia and the design landscape.

1.9 Dissertation Layout

This dissertation begins in Chapter 1 by providing some background on sustainable development and why more work is needed to ensure a healthy and habitable planet for future generations. It then provides the current extent of humankind's impact on the global environmental crisis along with some potential solutions to these problems by utilizing the evolutionary knowledge found in ecosystems through the understanding of their principles and properties.

We then delve into how these principles and properties can be measured through mathematical modeling in Chapter 2, and how these models can be pushed further to uncover a more fundamental understanding behind the sustainable organization of ecosystems in Chapter 3. We examine the metrics ecologists have already studied for decades to try and see which of these metrics, or combination of metrics, can be used to provide predictive insight into their sustainable configurations for use in the engineered world. This is accomplished by using data discovery methods from multivariate statistics to include correlation analysis, principle component analysis, and cluster analysis. Next, the dissertation explores how engineered systems components can mimic the functionality of the key recycling components found in natural ecosystems. We present a classified and characterized database for students, researchers, and industrial professionals to use, contribute, or gain inspiration from in Chapter 4. We then provide an example of the environmental, social, and economic design considerations one might explore when using the database.

The dissertation then defines and presents the core of the proposed ENA modeling framework, the system component in Chapter 5. Next, the general modeling framework is introduced and applied to two case studies in automobile manufacturing and carpet manufacturing networks. These case studies serve to illustrate the challenges in both initial model formulation (automobile manufacturing) and late stages of the modeling framework (carpet manufacturing). These include system boundary definition, initial assumptions, structural model development and calculation, scenario exploration with the incorporation of ecological, technological, or hybrid interventions from the database, the expansion of the model to include flow-based metrics, and the incorporation of economic factors and optimization into the model. Finally, the dissertation explores the application of the modeling framework applied from top to bottom with an example of the steel manufacturing in Chapter 6. This case study explores all aspects of the proposed design methodology in-depth from initial model formulation, to structural and flow-based analysis, and finally cost and feasibility analysis.

1.10 In Summary

This chapter outlines the research goals, fundamental contributions, and ultimate execution of a research plan for completion of the ensuing dissertation. As shown, there is a foundation for using biologically inspired design methods to analyze and measure the performance of engineered systems. This dissertation builds on that foundation by looking to the knowledge found in the intricate decomposing networks of mature natural ecosystems. Further, we then provide a template for further application and refinement of engineered systems using these decomposing networks.

A generalized mathematical modeling methodology for any engineered system and its subcomponents commences the proposed analysis. Mature natural ecosystems assist in identifying

the missing structural and flow-based principles and properties in this mathematically modeled engineered system through statistical analysis and an algorithmic approach. A collection of technological, biological, or hybrid systems identified to fit the missing cycling or decomposer roles augment the modeled system to address material or energy performance gaps. Testing and validation of this methodological approach on varying engineered systems ensure flexibility in application across the design landscape.

The outcome of this research will address a need in the design community for a systematic methodology and application in the proper identification and utilization of these essential decomposing systems that may then be adapted to any modeled system. This research will further the use of the ENA method and continue to test its effectiveness in sustainable network design by adapting modeling and analysis into a design tool.

CHAPTER 2. LITERATURE REVIEW

In the following sections, we present society's effort in addressing global environmental challenges and some potential solutions. We begin by exploring the progression of sustainable development through time. In addition, we identify and present the sustainable principles and properties that mature natural ecosystems possess. Finally, we address how some engineers and scientists leverage these lessons from natural systems by incorporating technological and ecological systems into their designs and some cutting-edge mathematical techniques that may be used to further this approach.

2.1 Sustainable Development in the Engineered World

The idea and progression of the world towards more sustainable development evolved over time with many pivotable moments, typically brought about by some environmental or technological event. In the following sections, we share some of these defining moments and show some of the steps that humankind is currently pursuing to ensure a healthy and habitable planet for future generations.

Industrial activity was not widespread prior to 1750, and history suggests no global resource pillaging, as individual craftsman manufactured goods in limited supply. It wasn't until the technological advancements made possible by coal and iron mining and manufacturing that resource scarcity emerged as an issue. This industrial revolution resulted in steam engines, high quality tools and machines, bridges, ships, and eventually to mechanized agriculture. These inventions opened reliable trade routes over large areas

and allowed for a shift from an agrarian society to a more urban society. This shift has resulted in massive population increase and a corresponding increase in atmospheric greenhouse gasses Carbon Dioxide, Nitrous Oxide, and Methane as demonstrated in Figure 2 below.

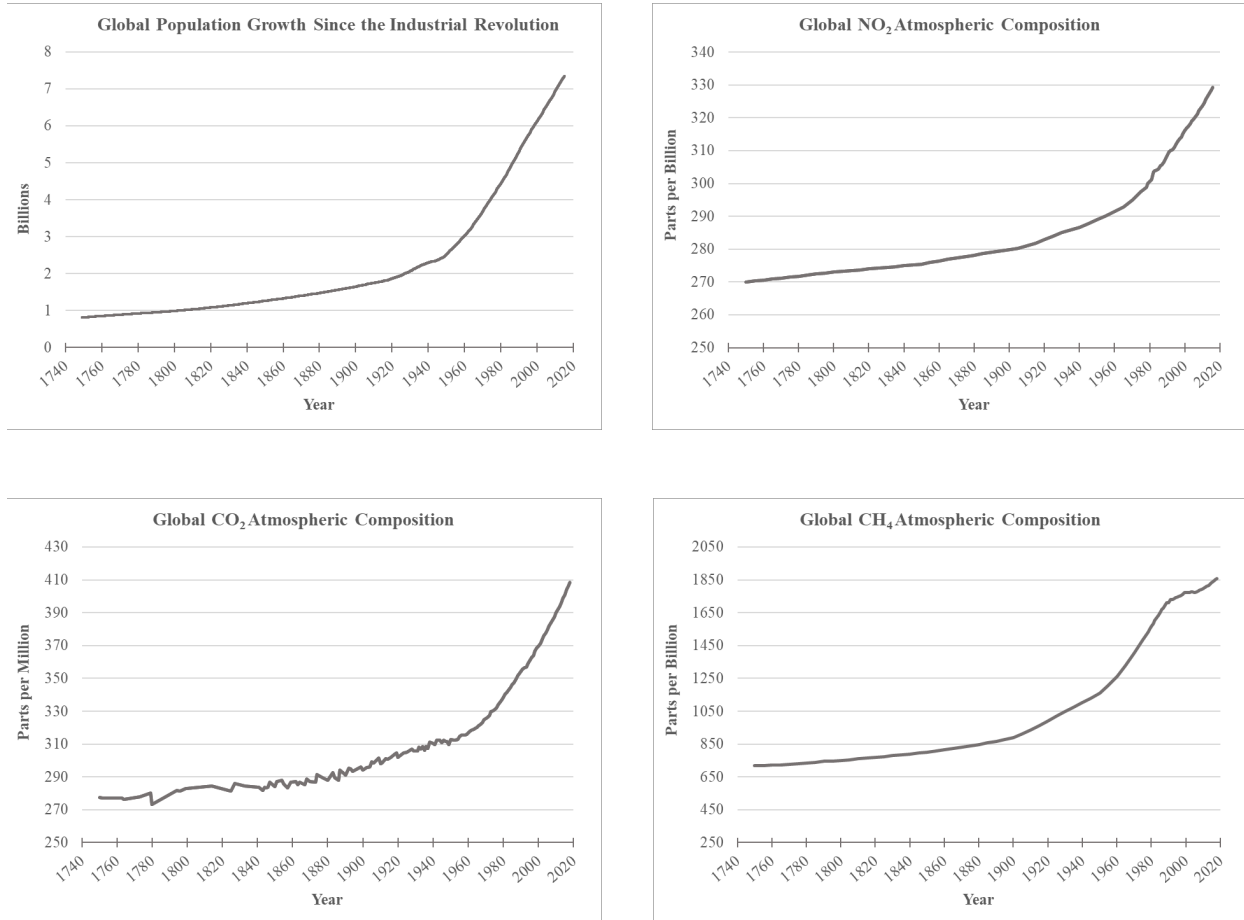


Figure 2. Growth in Population and Atmospheric Greenhouse Emissions Since the Beginning of the Industrial Revolution. Top Left: The Global Population Growth (Klein Goldewijk, Beusen, & Janssen, 2010; Kremer, 1993; United Nations, 2019). Bottom Left: The Global Atmospheric Composition of Carbon Dioxide (Bernhard Bereiter et al., 2015). Top Right: The Global Atmospheric Composition of Nitrous Dioxide ((EEA, 2018). Bottom Right: The Global Atmospheric Composition of Methane (European Environment Agency (EEA) & (NOAA), 2019).

The United Nations in 1983 created an independent organization named the World Commission on Environment and Development led by Gro Harlem Brundtland to identify,

raise awareness, and suggest solutions to these growing sustainability problems worldwide. This Brundtland Commission was one of the first global attempts at uniting the countries of the world around the idea of sustainable development. The definition of sustainability, or the sustainable development of the human-engineered world, varies widely in literature today. However, the Brundtland Commissions definition is most common and found in their published work “Our Common Future” in 1987. The Commission defined sustainability as meeting the needs of the present, without compromising the ability of future generations to meet their own needs (Brundtland, 1987).

Since the publication of Our Common Future, the global population has increased from 5 billion people to 7.8 billion in 2020 and is projected to be 8.5 billion by 2030 (United Nations, 2019). This population increase places extreme hardship on natural ecosystems and resources from increased demand for water, energy, industrial output, and food (Crutzen, 2006; Daily, 1997). The United Nations put forth 17 Sustainable Development Goals in 2015 to be achieved by the year 2030 to address these global challenges. These goals seek to achieve a better social, economic, and environment for the world (United Nations, 2015).

Similarly, the United Nations Framework Convention on Climate Change spawned The Paris Agreement signed in 2016, which is an agreement between 195 countries to work together in keeping anthropogenic climate change below 2°C (Bodansky, 2016). Despite worldwide concurrence on the pursuit of this sustainable future, one government and their people fail to recognize the planet has a finite source of capital stock, and the United States withdrew from the Paris Agreement in 2017 to continue normal means of production and

consumption citing potential economic burden (Boulding, 1966; Pompeo, 2019). Though the reintegration of the United States into the agreement may occur, the move reflects a common assumption throughout recent history of limitless raw materials, yet a more sustainable future requires a shift from open-ended economics to a circular economic system (Djuric Ilic, Eriksson, Ödlund, & Åberg, 2018; Laird, 2017).

2.2 Organizing Principles of Ecosystems

2.2.1 Evolution and Sustainability in Food Webs

Over the period of 3.8 billion years, natural ecosystems have evolved through periods of material and energy shortages to sustainable configurations, where organic materials move through functional roles of producers, consumers, and finally returned to the system through decomposers (B. D. Fath & Haines, 2007). The basic configuration of these natural systems are often represented as a pyramid, as illustrated in Figure 3 (Brian D. Fath, 2008).

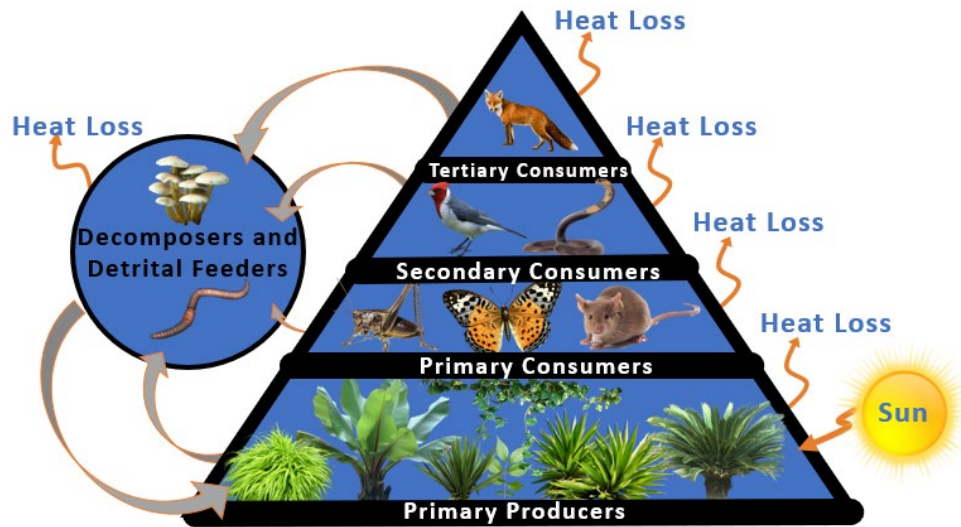


Figure 3. Ecosystem Functional Roles

This pyramid reflects the amount of biomass or energy of different functional groups in ecosystems and how energy moves between these groups. Primary producers, such as plants, use solar energy and nutrients from the soil to produce plant biomass. Decomposing organisms that feed on dead organic matter, or detritus, partially supply these nutrients (Mitsch & Jørgensen, 2003). The second level in the pyramid is primary consumers such as herbivores and secondary consumers such as omnivores. These organisms maintain their energy supply by feeding on the organisms in the base of the pyramid. The smallest group at the top of the pyramid are the carnivorous organisms that consume the primary consumers. A food chain represents the movement of energy when one organism consumes another from one trophic level to the next. However, organisms may function as both carnivores and herbivores (omnivores), so consumer interactions are best thought of like a Food Web (FW) as illustrated below in Figure 4.

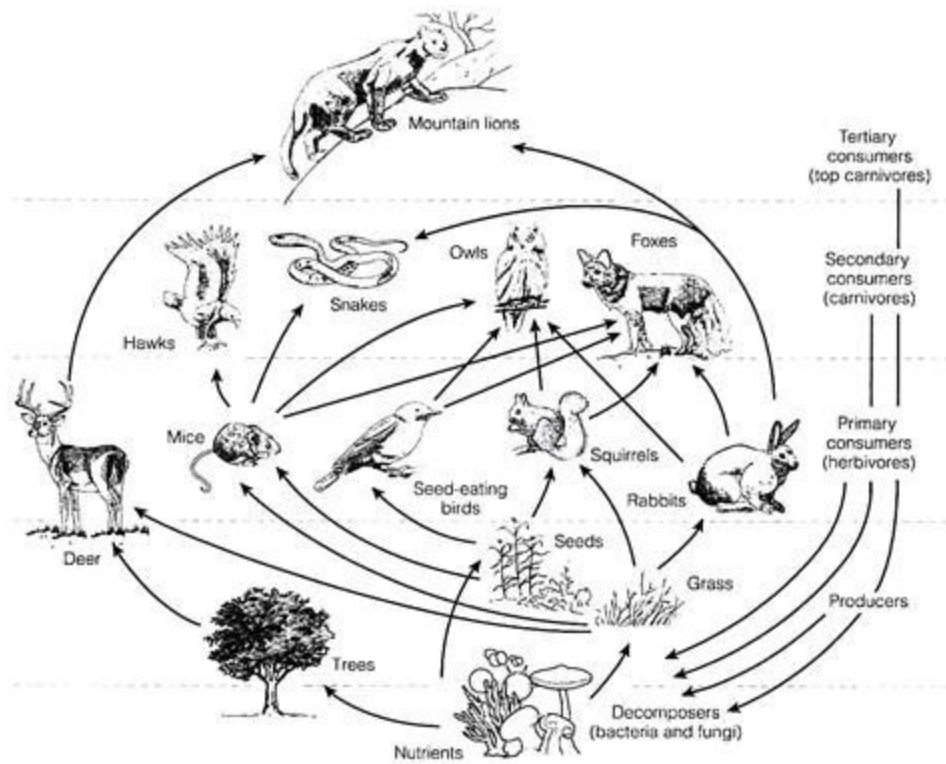


Figure 4. Food Web Interpretation of Ecosystem (Meghna, 2020)

2.2.2 The Importance of Detrital Actors and the Decomposer Functional Role in Ecosystems

The decomposer functional role (e.g. detrital actors, detritivores) from Figure 3, consisting of decomposers (e.g. fungi) and detrital feeders (e.g. earthworms, slugs, millipedes, etc.), is vital to natural ecosystems by promoting material and energy recycling (Moore et al., 2004). Some studies have shown that detrital actors can be involved with over half of the material flows within an ecosystem (Carrer & Opitz, 1999). The importance of these members of an ecosystem cannot be understated. Ecologists have shown that the inclusion of the detrital actors into ecosystems causes additional energy to be available, which impacts the biodiversity, food web structure, and the transient responses of ecosystems.

These decomposers accomplish this by converting dead organic matter and waste from all trophic levels into inorganic nutrients that fertilize the growth of the producers (Bergon, Harper, & Townsend, 1986; Freedman, 1998). These decomposers typically consist of an array of bacteria and fungi that absorb and metabolize the material flows in natural systems, breaking complex organic tissue into the fundamental components of carbon dioxide, water, and inorganic nutrients that can then be re-introduced as food to the higher trophic level consumers in the ecosystem (Carrer & Opitz, 1999). In addition, decomposers are often biochemically specialized to consume organic materials and waste products that are difficult for other organisms to digest (Geng & Côté, 2002).

2.3 Graph Theory – Principles and Applications in Ecology and Engineered Networks

The mathematical modeling in this dissertation relies on the fundamentals found in graph and information theory. The following sections describe the basics needed to understand ecological metrics and how they relate to graphs.

2.3.1 Principles of Graph Theory

The origin of graph theory is traced back to 1735 when Leonhard Euler was presented with the famous mathematical problem involving the Seven Bridges of Königsberg (S G Shrinivas, Vetrivel, & Elango, 2010). The problem was how to construct seven bridges in the city of Königsberg in such a manner that once may walk the entirety of the city, which consisted of a river-split city and two large islands, while only crossing each bridge once. Euler proved the problem has no solution by reformulating the problem in abstract terms. Each land mass took the form of a node, and each bridge and edge. The abstraction process is demonstrated below in Figure 5.

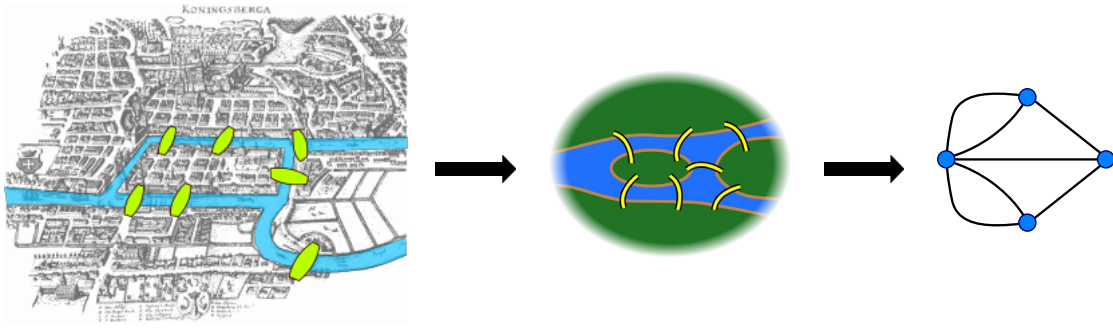


Figure 5. Graph Theory Origins – Euler's Bridges

Since Euler's bridge problem, the theoretical concepts behind graph theory have grown and are used in many fields of research today. These fields include the study of the construction of bonds in chemistry, the interactions amongst species in Biology and Ecology, operations research, computer science, and much more (Pavlopoulos et al., 2011; Platt, Mann, & Ulanowicz, 1981; S G Shrinivas et al., 2010).

In graph theory, a graph is two nodes connected by an edge. These nodes in a graph can be connected in any possible way, typically denoted $\langle i, j \rangle$, where i is the source (origin) node and j is the destination node (Henley, 1973). Graphs can be categorized based on the information their edges contain. Predominantly, edges can either have direction (flow), or be undirected. In directed graphs, also known as digraphs, there is only one path between two nodes. In undirected graphs, the path between nodes is bidirectional (Kumar & Pattnaik, 2018).

In mathematics, graphs typically take the form $G=(V,E)$ where V is a set of nodes (also known as vertices) and E are a set of edges (also known as links). The hierarchy of the G does not matter with undirected graphs but does matter with directed graphs. The

major role of graph theory in computer applications is the development of graph algorithms. Some of the algorithms are as follows (S G Shrinivas et al., 2010):

1. Shortest path algorithm in a network
2. Finding a minimum spanning tree
3. Finding graph planarity
4. Algorithms for finding adjacency matrices
5. Algorithms to find connectedness
6. Algorithms to find cycles in a graph
7. Algorithms for searching for an element in a data structure

The following sections explore how graphs are used in the field of Ecology, and how algorithms may be used to calculate graph similarity or match graph structures to others.

2.3.2 *Ecological Network Analysis (ENA)*

Ecological Network Analysis (ENA) is a quantitative tool used by ecologists to study interactions within ecosystems in a holistic manner (J T Finn, 1977; R. E. Ulanowicz, 1983). ENA derives structural and functional properties of ecological systems using graphs to represent FW interactions. These graphs consist of nodes and edges that represent predator-prey exchanges of material and energy. The calculation of these structural metrics involves the identification of predators, prey and the links they represent in a FW. A one denotes a successful link in a matrix representation of the FW graph and zero denotes the absence of a link with columns representing predators and rows representing prey (i.e. $f_{ij} = 1$ represents a link between prey (i) and predator (j)); The species are numbered and listed above and beside the matrix to show they are the same species across rows and columns.

The nomenclature for the network metrics used in this thesis originate from multiple sources but have been compiled by Kones, Soetaert, Van Oevelen, and Owino (2009) and are shown below in Table 1.

Table 1. Nomenclature and Symbols Used in the Calculation of Network Indices

Term	Description
n	Number of internal compartments in the network, excluding 0 (zero), $n + 1$ and $n + 2$
$j = 0$	External source
$i = n + 1$	Usable export from the network
$i = n + 2$	Unusable export from the network (respiration, dissipation)
T_{ij}	Flow from compartment j to i , where j represents the columns of the flow matrix and i the rows
T_{ij}^*	Flow matrix, excluding flows to and from the external
T_i	Total inflows to compartment i
T_j	Total outflows from compartment j
T_i	Total inflows to compartment i excluding inflow from external sources
T_j	Total outflows from compartment j , excluding outflow to external sources
$(\dot{x}_i)_-$	A negative state derivative, considered as a gain to the system pool of mobile energy
$(\dot{x}_i)_+$	A positive state derivative, considered as a loss from the system pool of mobile energy
z_{i0}	Flow into compartment i from outside the network
y_{n+j}	Flow out of the network for compartment j to compartments $n + 1$ and $n + 2$
c_{ij}	The number of species with which both i and j interact divided by the number of species with which either i or j interact
I, δ_{ij}	Identity matrix and its elements

Table 2 below uses the definitions from Table 1 above and gives several network measures that include some General Indices, Pathway Analysis, Network Uncertainty, and a Systems Development and Growth.

Table 2. Network Index Codes and Formulas.

NETWORK MEASURE	INDEX NAME	CODE	FORMULA	SOURCE(S)
GENERAL INDICES	Total system throughput	$T_{..}$	$\sum_{i=1}^{n+2} \sum_{j=0}^n T_{ij}$	Hirata and Ulanowicz (1984)
	Total system throughflow	TST	$\sum_{i=1}^n \sum_{j=1}^n [T_{ij} + z_{i0} - (\dot{x}_i)_-] = \sum_{i=1}^n \sum_{j=1}^n [T_{ij} + y_{n+j} - (\dot{x}_i)_+]$	Latham (2006)
	Number of links	L	$\sum_{i=1}^{n+1} \sum_{j=0}^n (T_{ij} > 0)$	Latham (2006)
	Link density	LD	L/n	Latham (2006)
	Generalization	G	$\frac{L}{n_{prey}} \text{ where } n_{prey} = \sum_{i=1}^n \begin{cases} 1 \text{ for } \sum_{j=1}^n T_{ij} > 0 \\ 0 \text{ for } \sum_{j=1}^n T_{ij} = 0 \end{cases}$	Schoener (1989)
	Vulnerability	V	$\frac{L}{n_{predators}} \text{ where } n_{predator} = \sum_{j=1}^n \begin{cases} 1 \text{ for } \sum_{i=1}^n T_{ij} > 0 \\ 0 \text{ for } \sum_{i=1}^n T_{ij} = 0 \end{cases}$	Schoener (1989)
	Connectance	C	$\frac{L_{int}}{n(n-1)} \text{ where } L_{int} = \sum_{i=1}^{n+1} \sum_{j=0}^n (T_{ij} > 0)$	Latham (2006)
	Average link weight	\bar{T}_{ij}	$T_{..}/L$	Pimm and Lawton (1980)
	Average compartment throughflow	\overline{TST}	TST/n	Latham (2006)
	Compartmentalization	\bar{C}	$\frac{L_{int}}{n(n-1)} \sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq 0}}^n c_{ij}$	Pimm and Lawton (1980)

Table 2. (Continued)

PATHWAY ANALYSIS	Total system cycled throughflow	TST_c	$\sum_{j=1}^n \left(1 - \frac{1}{q_{ij}}\right) T_j \text{ where } Q = (I - G')^{-1} \text{ where } G^{-1} = \left[\frac{T_{ij}^*}{\max(T_i, T_j)} \right]$	J. T. Finn (1976); J T Finn (1977); John T. Finn (1980); Patten, Bosserman, Finn, and Cale (1976); Patten and Higashi (1984)
	Total system non-cycled throughflow	TST_s	$TST - TST_c$	J. T. Finn (1976); J T Finn (1977); John T. Finn (1980); Patten et al. (1976); Patten and Higashi (1984)
	Finn's cycling Index	FCI	$\frac{TST_c}{TST}$	J. T. Finn (1976); J T Finn (1977); John T. Finn (1980); Patten et al. (1976); Patten and Higashi (1984)
NETWORK UNCERTAINTY	Average path length	\overline{PL}	$\frac{TST}{\sum z_{i0} - \sum (\dot{x}_i)_-} = \frac{TST}{\sum y_{n+j} + \sum (\dot{x}_i)_+}$	J. T. Finn (1976); J T Finn (1977); John T. Finn (1980); Patten et al. (1976); Patten and Higashi (1984)
	Average mutual information	AMI	$\sum_{i=1}^{n+2} \sum_{j=0}^n \frac{T_{ij}}{T_{..}} \log_2 \frac{T_{ij} T_{..}}{T_i. T_{.j}}$	Robert E. Ulanowicz (2004)
	Statistical uncertainty	H_R	$- \sum_{j=0}^n \frac{T_{.j}}{T_{..}} \log_2 \frac{T_{.j}}{T_{..}}$	Latham (2006), Robert E. Ulanowicz and Norden (1990)
	Conditional uncertainty	D_R	$HR - AMI$	Latham (2006), Robert E. Ulanowicz and Norden (1990)
	Realized uncertainty	RU_R	$\frac{AMI}{H_R}$	Latham (2006), Robert E. Ulanowicz and Norden (1990)

Table 2. (Continued)

SYSTEM'S DEVELOPMENT AND GROWTH	Network constraint	H_c	$\sum_{i=1}^n \log_2(n+2) - \left[- \sum_{i=1}^{n+2} \sum_{j=1}^n \frac{T_{ij}}{T_{..}} \log_2 \frac{T_{ij}}{T_{.j}} \right]$	Latham (2006), Robert E. Ulanowicz and Norden (1990)
	Constraint efficiency	CE	$\frac{H_c}{H_{max}}$	Latham (2006), Latham and Scully (2002)
	Ascendency	A	$AMI \times T_{..} = \sum_{i=1}^{n+2} \sum_{j=0}^n T_{ij} \log_2 \frac{T_{ij} T_{..}}{T_{i.} T_{.j}}$	Robert E Ulanowicz (2000); Robert E. Ulanowicz and Norden (1990)
	Development capacity	DC	$- \sum_{i=1}^{n+2} \sum_{j=0}^n T_{ij} \log_2 \frac{T_{ij}}{T_{..}}$	Robert E Ulanowicz (2000); Robert E. Ulanowicz and Norden (1990)
	Overhead	ϕ	$DC - A$	Robert E Ulanowicz (2000); Robert E. Ulanowicz and Norden (1990)
	Extent of development	AC	$\frac{A}{DC}$	Robert E Ulanowicz (2000); Robert E. Ulanowicz and Norden (1990)

The structure and flow-based metrics calculations shown above are covered extensively in literature (Brian D. Fath et al., 2007; J. T. Finn, 1976; A. Layton, B. Bras, & M. Weissburg, 2016; Stephen M. Malone, 2017; Stephen M. Malone et al., 2018; Sven Erik Jørgensen, 2009; R. E. Ulanowicz, 1983; Robert E Ulanowicz, 2000). Table 3 below provides a short definition for each metric for conceptual understanding:

Table 3. Description of ENA Measures

NETWORK MEASURE	INDEX NAME	CODE	DESCRIPTION
GENERAL INDICES	Total system throughput	$T_{..}$	The sum of all flows in an ecosystem. This is a measure of size or level of activity (similar to GNP, which estimates the overall economic activity of a nation)
	Total system throughflow	TST	the sum of compartmental throughflows
	Number of links	L	The number of direct links between species in a FW. This term is represented by the number of nonzero interactions in the FW matrix
	Link density	LD	The ratio of the total number of links to the total number of species within a network
	Generalization	G	The average number of preys consumed per predator within the food web. This is calculated by the summation of the columns in a food web matrix, and then dividing the number of columns with non-zero elements ($n_{predators}$).
	Vulnerability	V	The average number of predators per prey in a system. This is calculated by the summation of the rows in a system, then dividing by the number of rows with non-zero elements (n_{prey}).
	Connectance	C	The number of actual direct interactions (L) in a FW divided by the total number of possible interactions (N^2). If one forbids cannibalism, then the number of possible interactions is diminished, resulting in the denominator becoming the fraction of non-zero off-diagonal elements in the FW
	Average link weight	\bar{T}_{ij}	The total system throughput normalized by the number of links in a system
	Average compartment throughflow	\overline{TST}	The average throughflow per compartment in the system
	Compartmentalization	\bar{C}	The values range between 0 and 1, and measures the degree of connectedness of subsystems within a network, with higher values indicating stronger subsystems
PATHWAY ANALYSIS	Total system cycled throughflow	TST_c	The total amount of cycled throughflow in a system
	Total system non-cycled throughflow	TST_s	The total amount of non-cycled throughflow in a system
	Finn's cycling Index	FCI	Dimensionless number that accounts for percentage of all fluxes generated by cycling, or the fraction of total activity in the system that is devoted to cycling
	Average path length	\overline{PL}	The number of actors "visited" by a material or energy flow before leaving the system

Table 3. (Continued)

NETWORK UNCERTAINTY	Average mutual information	AMI	The degree of specialization in the system or the amount of constraints on the materials and or energy flow, measured as the amount of flow between two compartments relative to the sum of the total flow passing through both compartments. AMI has been suggested as being indicative for the developmental status, or level of system maturity of an ecosystem
	Statistical uncertainty	H_R	The upper bound of AMI and measures diversity in the system
	Conditional uncertainty	D_R	Measures degree of stability of a system
	Realized uncertainty	RU_R	The proportion of total uncertainty accounted by the network structure as measured by the AMI. Realized uncertainty is useful in comparing the degree of constraint across systems
	Network constraint	H_C	The constraint inherent in the network
	Constraint efficiency	CE	A scale independent ratio of the constraint inherent in the network to the maximum uncertainty for the network if all compartments were connected with evenly distributed flow magnitudes.
SYSTEM'S DEVELOPMENT AND GROWTH	Ascendency	A	Measures the amount of medium that an ecosystem distributes in an efficient way. Thus, providing a single measurement of growth and development inherent in the system
	Development capacity	DC	The maximum potential that a system has at its disposal to achieve further improvements, and also serves as an upper bound for A
	Overhead	ϕ	Overhead pertains to redundant flows in the network and might be an indicator as to the point of optimality between flexibility and efficiency
	Extent of development	AC	The ratio of ascendency to development capacity is interpreted as a measure of extent of the systems' development

These metrics originate from graph and information theory branches of mathematics, describing simple structural calculations such as Linkage Density, to more complex flow-dependent properties such as Ascendency, Development Capacity, and Finn Cycling Index. This proposal focuses on the metrics that identify cycling behavior and specifically the components of natural ecosystems that comprise the decomposer functional role, as 70-80% of all primary production in ecosystems eventually enters this detrital

feedback loop (O'Neill R. V. & Reichle, 1979; Eugene P. Odum & De La Cruz, 1963; Wetzel & Ward, 1992).

2.3.3 Previous Ecological or Bio-Inspired Design Applications to Engineered Systems in Literature

Biologically Inspired Design (BID) is a method of looking to nature for a solution to some engineering problem (French, 1994). This solution could be aesthetic, structural, functional, systematic, or of many more types. The idea of BID has been around for some time and assumes that biological systems have evolved over time and adapted over many generations, and thus optimized for a particular task or environment. Below are a few examples of BID applied to vehicle manufacturing, but are in no way a comprehensive list of BID applications in industry:

2.3.3.1 Supply Chain Management

A bio-inspired framework has been developed to determine the right biological inspiration for a particular supply chain management (Fan, Zhang, Hapeshi, & Yang, 2014). This framework is based on the ability of animal groups to coordinate complex tasks using peer to peer communication in conjunction with a limited number of simple behavioural rules. The users of this framework select the requirements or characteristics of their supply chain management and this produces a list of bio-inspired principles that could be applied to their system. These principles are derived from ant and bee colonies, fish schooling, bird flocking, and others. Once these principles are applied, the various behaviours are intended to improve efficiency in the supply chain.

2.3.3.2 Bio-inspired Manufacturing System

Using the constant feedback and communication of the neuro-endocrine-immunity system found in biological organisms, a manufacturing cell was developed to achieve an intelligent and adaptable control system for automobile manufacturing (Tang, Wang, Gu, Yuan, & Tang, 2010). Modelled after the ultra-short feedback loop in the communication pathways between the brain and immune system, the bio-inspired manufacturing cell was able to overcome the often-slow communications between manufacturing system responses to a disruption.

2.3.3.3 Automobile Transmission Case

By mimicking the ability of animal groups (such as: bees, ants, termites) to coordinate and allocate complex tasks using peer to peer communication without depending on a central control platform, researchers have developed advanced manufacturing systems that adapt to disturbances brought about by things such as manufacturing tools breaking or wearing down, order cancellations, and priority changes (Park & Tran, 2013). This bio-inspired manufacturing system relies on communication and task allocation between system components, creating cognitive agents that can reason and make decisions based on real-time conditions. This gives machines the ability to communicate by indicating their readiness ability to perform tasks, and if this machine goes out of operation, then tasks in the overall system may

be diverted to other machines. This mitigates down time caused through system reorganization, limiting a large-scale disturbance in the overall system production. Overall, using this manufacturing approach led to reduced recovery times and increased system utilization.

Though there are plenty of examples of specific products and processes developed from biological systems (velcro, sharkskin, etc), this dissertation focuses on the systems level of biological systems for insight and inspiration through the use of ENA. ENA has been used in a number of case studies to quantify the performance of urban and industrial networks (Brehm, Chatterjee, & Layton, 2020; Brehm & Layton, 2020; Dave & Layton, 2020). In one such study, Zhang et al. analyzed the urban water network for Beijing and the urban energy networks of four different cities in China (Y. Zhang, Liu, & Fath, 2014; Y. Zhang, Zheng, et al., 2014). The authors created different compartments present within the cities in order to analyze the networks' structure and relationships. The water network compartments included the industrial sector, ecological environment, agricultural sector, rainwater collection system, wastewater regeneration system, and the domestic sector. The energy network had many more compartments but included entities such as oil refinery, construction, and household. The authors were able to calculate the contributions – or weight – of each compartment to the overall network using the flows between the different network compartments. These weights account for both the direct and indirect flows between the compartments and comparing them to the trophic levels can give information about the structure of the network. As shown, we know that in natural ecosystems the lowest trophic level (the decomposer functional role) consume the most amount of material with higher trophic levels consuming less and less material as the level increases. Using

this analysis, it can be determined if these systems exhibit the same pattern of consumption based on trophic level. Furthering the analysis, the authors used network utility analysis to understand the relationship between the different compartments. There has been a call to expand the analysis on these urban metabolism networks to include information indices in the metrics of ascendancy and development capacity (S. Chen, Fath, & Chen, 2010).

S. Chen and Chen (2015) have used ENA in conjunction with energy flow analysis and input-output analysis to look at the urban energy consumption in Beijing (S. Chen & Chen, 2015). This study used network control analysis, which investigates how components control one another through their inputs and outputs. Controlled energy is similar to embodied energy as it looks at the motivation behind the energy use. If the motivation behind energy consumption is from one sector but shows up as actually being consumed in another, this could incorrectly identify where the energy use originates. For example, the energy consumed in the transportation of goods will show up in the transport sector but is actually motivated by the sector for those goods, but it should be ascribed to the other sector in a network control perspective. Similar forms of the network analysis have been conducted for a natural gas network (Shaikh, Ji, & Fan, 2017), carbon metabolism network (Lu, Chen, Feng, & Hubacek, 2015), and overall urban metabolic network (Y. Zhang, Zheng, et al., 2014). These uses of ENA with urban metabolism highlight its potential to analyze large-scale networks, but it can be used at almost any level.

The idea of applying ecological principles to engineered systems is not new, and the application to industry may be traced to Robert Frosch in 1992 (Frosch, 1992). This

idea is to use the cyclical organization of plants and animals found in ecological systems and translate this organization to those of industrial systems in an effort to minimize waste. This is similar, but different to the idea behind industrial symbiosis, that seeks to co-locate industries that freely exchange and utilize waste streams for economic advantage (Chertow, 2004). A clear application of the ideas behind industrial ecology, circular economy, and those found in industrial symbiosis is in the development of Eco-Industrial Parks (EIPs). These EIPs seek to mimic the structure and functionality of ecosystems through their conceptual design (T. E. Graedel & Allenby, 1995).

2.4 Summary of Literature Review

This literature review gives a brief overview of some of the environmental problems in the world, sustainable design in engineering, and the fundamentals of ecosystems organize themselves. We addressed a key component of ecosystem functionality, the decomposer functional role, and how essential it is to a healthy ecosystem.

This chapter also introduces the principles of graph theory, how ecologists measure the performance of ecosystems using metrics, and finally how some engineers are using these metrics-driven approaches to uncover ecosystem principles and properties to design human-engineered systems.

CHAPTER 3. PATTERNS IN ECOSYSTEMS: FUNCTIONAL UNDERSTANDING AND MEASUREMENT

Ecologists have few tools to understand the macro level functions of how ecosystems operate (Robert E. Ulanowicz, 2004). The most common tool for understanding these functions is through simulation modeling. This is accomplished by breaking down the core functions and the interactions between these functions into a mathematical form, adjustment of these forms through model calibration, and validation of the model results. While some ecologists have been successful with this approach, the current state of ecosystem dynamic modeling leaves much to be desired, as the greater the interactions between species leads to the diminished power to predict through mechanisms such as compounding error, unrealistic assumptions, and the interactivity of nonlinear functions (Lorenz, 1963; Platt et al., 1981; Wulff & Ulanowicz, 1989).

As a result, some ecologists use an array of metrics as a different approach to understand the links between ecosystem structure and the resulting behavior of ecological systems (Brian D. Fath et al., 2007; Hirata & Ulanowicz, 1984; R. E. Ulanowicz, 1983; Robert E Ulanowicz, 2000; Robert E. Ulanowicz, 2004; Robert E. Ulanowicz et al., 2014). In the following sections, we describe our approach to aggregating a 100-ecosystem dataset, preprocessing this dataset for analysis, and how we use multivariate statistical methods to uncover how these metrics interact and how we can use these methods to gather high-level insight into ecosystem functionality. This high-level insight may then be used in translating ecosystem principles and properties to the built environment.

Through inspection of the mathematics behind the ecological metrics, it is believed some may be highly correlated and thus superfluous to the core metrics that describe ecosystem functionality. We believe a more targeted approach may be employed in translation to the built environment by pairing down the ecological metrics. We expect this will in turn facilitate a higher level of focus and ease of communication to decision makers in the design process.

3.1 Research Tasks and Goals to be Addressed

This chapter provides the structure to analyze engineered systems from an ecological perspective as stated in research goal 1.5.1 and RT1. These ecological systems from literature are of varying size and complexity and this chapter provides a means to rank the natural ecosystems based on network statistics.

3.2 Ecosystems from Ecobase

Ecopath with Ecosim is a modeling software package used to create models of marine and aquatic ecosystems. The software has been in continuous development since the 1980's and has been modified to include dynamic changes to modeled systems, spatial changes, and methods to compare modeled ecosystems using ENA (Heymans et al., 2016). Ecopath with Ecosim is the most applied tool in ecosystem modeling today, with over 400 ecosystems published. Due to its prolific use in Biology and Ecology, this database is a natural choice to serve as a repertoire for reference ecosystems used for this thesis.

3.2.1 *Network Extraction and Balancing*

The aquatic ecosystem models from Ecopath with Ecosim are of varying preparedness for analysis. First, the models must be extracted from the software so they may be aggregated, checked for steady state assumption through balancing, and ENA metrics calculated and analyzed using the data discovery methods discussed in section Multivariate Methods for Ecosystem Functioning. The following section describes the extraction technique, followed by balancing method, and metrics calculation.

Of the 433 unique ecological models found within Ecopath with Ecosim, only 133 had data available through the database management system of the software, Ecobase (Colléter et al., 2015). Unfortunately, there is no mass export functionality of embedded databases currently available through the Ecopath with Ecosim software package. Therefore, these 133 ecosystems were exported manually through the software on an individual basis. The extracted ecosystem model data is stored in databases of a modified Microsoft Access database file format. These databases were parsed and the underlying data extracted using an combined open source implementation of Ecopath in the MATLAB programming language (A. Kearney, 2017) and a short subroutine written for this thesis that may be found in the Appendix A.1 MATLAB Subroutine. The open source implementation was useful in digesting the tedious file format the ecosystems were originally stored in (a customized MS Access Database).

In addition, the Ecopath software performs the essential function of balancing the model. A modeled ecological system must be balanced before being transcribed to its graphical form and ENA metrics calculated as to preserve the fundamental principles of

conservation of mass and energy. The MATLAB implementation developed by A. Kearney (2017) proved useful to apply the best model balancing practices known in the construction and use of Ecosim ecosystem models (Heymans et al., 2016).

3.3 Multivariate Methods for Ecosystem Functioning

The array of indices used by ecologists to understand macro-level ecosystem functions leads one to the following question when seeking to translate these metrics for use in an engineering context:

What is the ecological metric, or combination of metrics, that best reflect ecosystem functionality for the design of more sustainable systems by mimicking ecosystem functionality?

This question assumes ecosystem functionality is a clearly defined as it relates to design. However, ecosystems are not intentionally designed and therefore do not exist in a design sense. Therefore, we define functionality as the emergent traits that are derived from the interactions among species in an ecosystem. This question is at the center of answering the overall research question of this dissertation. The following section seeks to break this question down into two parts.

1. Which metrics can be excluded due to their high level of correlations, as defined by the Pearson Product-Moment Correlation in section 3.3.1? As one may have observed, some of the ecological metrics are of similar construction and may yield nearly the same amount of information as a result. Once we determine that the

analysis does not benefit from the inclusion of the highly correlated metrics, we can then drop them and simplify our explanation of the results.

2. Which combination(s) of the remaining metrics best explain the variance in the ecosystem datasets? We are seeking to emulate ecosystem functionality, and as a result, we need to determine the metrics(or combination of metrics), that accurately reflect this functionality. Principle Component Analysis (PCA) is a proven statistical tool to accomplish this task.

The following section also summarizes and tests the strengths between the ecological metrics.

3.3.1 *Correlations of Food Web Metrics in Ecosystems*

The following correlation calculations are based on the Pearson Product-Moment Correlation (Jolliffe, 2002). This correlation coefficient measures the strength of the linear relationship between two variables. For response variables x and y , the Pearson product-moment, denoted as r , is computed as follows:

$$r = \frac{\sum (x - \bar{x}) (y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2} \sqrt{\sum (y - \bar{y})^2}}$$

where \bar{x} is the mean of x and \bar{y} is the mean of y

The correlation returns a value between negative one and positive one, with negative one being an exact negative correlation and positive one being an exact positive correlation. If there is low correlation the result is close to zero and no correlation the result equals zero.

We used the 100 ecosystems presented in Appendix A.2 Ecosystems and conducted a correlation analysis using the Pearson Product-Moment Correlation shown above across all of the metrics defined in Table 2. The Pearson Product-Moment Correlation results are shown below in Figure 6. The bottom left partition shows the data points along with their 95% bivariate normal density ellipse. Assuming that each pair of variables has a bivariate normal distribution, this ellipse encloses approximately 95% of the points. The narrowness of the ellipse reflects the degree of correlation of the variables. If the ellipse is fairly round and is not diagonally oriented, the variables are uncorrelated. If the ellipse is narrow and diagonally oriented, the variables are correlated. The diagonal of the plot shows the frequency histogram of the ecological metric where the top right partition shows the degree of correlation. The higher the degree of correlation, the larger the circle size and the color shade represents the degree of positive (brown) or negative (green) correlation.

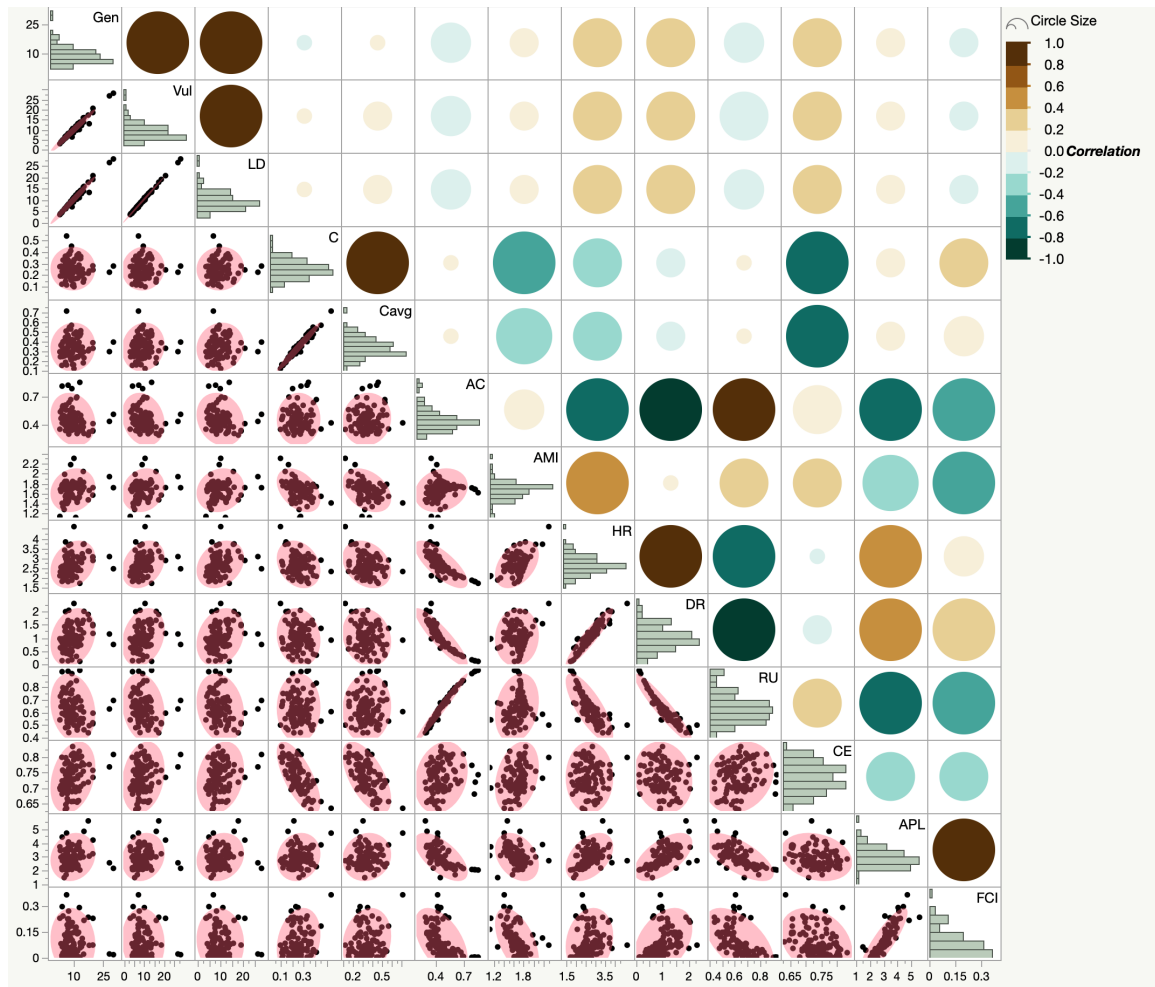


Figure 6. Pearson Product Moment Correlations Amongst Food Web Metrics. The Rows and Columns Titles are Labeled Across the Diagonal.

Figure 6 shows the ecological metrics Generalization (Gen), Vulnerability (Vuln), and Linkage Density (LD) have strong positive correlations with one another with large dark brown circles. Also, Connectance (C) and Compartmentalization (Cavg) are highly positively correlated. In addition, metrics such as Statistical Uncertainty (HR) and Conditional Uncertainty (DR), Extent of Development (AC) and Realized Uncertainty (RU), and Average Path Length (APL) and Finn Cycling Index (FCI) are all highly positively correlated. Metrics demonstrating a strong negative correlation (large green circles) include Connectance (C) and Compartmentalization (Cavg) with Constraint

Efficiency (CE), Conditional Uncertainty (DR) with Realized Uncertainty (RU), Conditional Uncertainty (DR) with Extent of Development (AC), and Extent of Development (AC) and Realized Uncertainty (RU) with Average Path Length (APL).

3.3.2 *Ecological Metrics Outlier Exploration*

As with any data exploration endeavors, one should investigate the possibilities of outliers in datasets. As mentioned previously in the Research Limitations and Assumptions of this dissertation, it is not the goal of this work to critique or correct the accuracy of the models developed by field ecologists. This work seeks to use best practices with analyzing the data created by ecologists, but only investigate their suitability for analysis in this thesis by traditional statistical methodology. One such methodology for outlier detection in multivariate statistics is the Mahalanobis distance.

The Mahalanobis distance takes into account the correlation structure and scale of the data. The Mahalanobis distance depends on the estimates of the mean, standard deviation, and correlation for the data. The distance is plotted for each observation in the data. For each value, the Mahalanobis distance, M_i , is calculated as:

$$M_i = \sqrt{(Y_i - \bar{Y})' S^{-1} (Y_i - \bar{Y})}$$

Where:

Y_i is the data for the i^{th} row

\bar{Y} is the row of means in the data

S is the estimated covariance matrix for the data

The Upper Control Limit (UCL) line in the Mahalanobis Distance plot in Figure 7 is a measure that relates to contours of the multivariate normal density with respect to the correlation structure (Mason & Young, 2002). The greater the distance from the center, the higher probability that the data point is an outlier. Figure 7 demonstrates the Mahalanobis Distance plot for the 100 ecosystems and metrics presented in Figure 6.

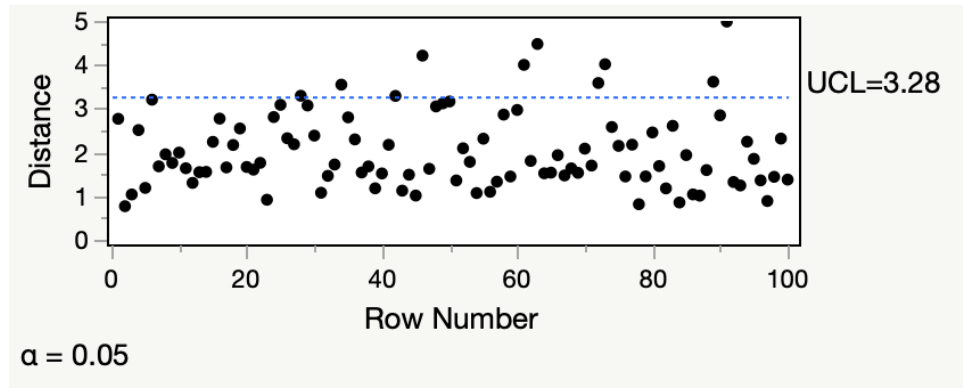


Figure 7. Outlier Detection Using Mahalanobis Distance

This UCL is calculated as follows:

$$UCL = \sqrt{\frac{(n-1)^2}{n}} \beta_{[1-\alpha, \frac{p}{2}, \frac{n-p-1}{2}]}$$

where:

n = number of observations

p = number of variables (columns)

$\beta_{[1-\alpha, \frac{p}{2}, \frac{n-p-1}{2}]} = (1-\alpha)^{th}$ quantile of a $Beta(\frac{p}{2}, \frac{n-p-1}{2})$ distribution

Multiple studies have demonstrated the Mahalanobis distance follows the Beta distribution when the confidence intervals for the where the sample mean and covariance matrix are

estimated by including the possible outlying points (Thennadil, Dewar, Herdsman, Nordon, & Becker, 2018).

As one may observe in Figure 7, 12 of the 100 ecosystem data points lie above the UCL line with a value of 3.28. Therefore, these ecosystems warrant further investigation to make sure their impact does not skew the results from future analysis. The outlier ecosystems are presented in Table 4 vary in study year, geographic location, and author.

Table 4. Potential Outliers of the 100 Ecosystems Multivariate Analysis

Model Name	Author	Period	Location	Associated Publication
Black Sea	Gucu, A.	1990-1991	Not Affiliated	Gucu A.C.(2002). Can Overfishing be Responsible for the Successful Establishment of <i>Mnemiopsis leidyi</i> in the Black Sea? <i>Estuarine, Coastal and Shelf Science</i> . pp 439-451
Schlei Fjord	Nauen, C.	1980-1981	Germany	Christensen V.,Pauly D.(1992). The ECOPATH II - a software for balancing steady-state ecosystem models and calculating network characteristics <i>Ecological Modelling</i> . pp 169-185
Gulf of California	Lercari, D.	1990-2000	Mexico	Lercari D.,Arreguin-Sánchez F.(2009). An ecosystem modelling approach to deriving viable harvest strategies for multispecies management of the Northern Gulf of California Aquatic Conservation: <i>Marine and Freshwater Ecosystems</i> . pp 384-397
Icelandic shelf	Mendy, A.	1997-1998	Iceland	Mendy, A. and E. Buchary (2001). Constructing an Icelandic Marine Ecosystem Model for 1997 Using a Mass-Balance Modelling Approach: 182-197.
Jurien Bay	Lozano-Montes, H.M.	2007-2008	Australia	Lozano-Montes H.M.,Loneragan N.R.,Babcock R.C.,Jackson K.(2011). Using trophic flows and ecosystem structure to model the effects of fishing in the Jurien Bay Marine Park, temperate Western Australia <i>Marine and Freshwater Research</i> . pp 421-431
Liberia	Kay, D.W.	2005-2006	Liberia	Kay D.W.(2011). Liberia report on Ecopath modeling Ecosystem-based fisheries management using Ecopath with Ecosim (EwE) software. pp 105-118. In Christensen V.,Villanueva C.
North South of China Sea	Cheung, W.W.L.	1970-1971	China,Vietnam	Cheung W.L.(2007). Vulnerability of marine fishes to fishing: from global overview to the Northern South China Sea
Northern Gulf of Mexico	Sagarese, S.	2005-2009	United States	Sagarese, S. R., et al. (2017). "Progress towards a next-generation fisheries ecosystem model for the northern Gulf of Mexico." <i>Ecological Modelling</i> 345: 75-98.
Prince William Sound	Okey, T.A.	1994-1996	United States	Okey T.A.,Wright B.A.(2004). Toward ecosystem-based extraction policies for Prince William Sound, Alaska: integrating conflicting objectives and rebuilding Pinnipeds <i>Bulletin of Marine Science</i> . pp 727-747
Raja Ampat	Ainsworth, C.H.	2005-2006	Indonesia	Pitcher T.J.,Ainsworth C.H.,Bailey M.(2007). Ecological and economic analyses of marine ecosystems in the bird's head seascape, Papua, Indonesia: I Fisheries Centre Research Reports

Table 7. (Continued)

Tampa Bay	Chagaris, David	2005-2010	United States	D. Chagaris & B. Mahmoudi, 2010. Assessing the influence of bottom-up and top-down processes in Tampa Bay using Ecopath with Ecosim. In: Cooper, S.T. (ed.). Proceedings, Tampa Bay Area Scientific Information Symposium, BASIS 5: 20-23 October 2009. St. Petersburg, FL. pp 263-274.
Thau	Palomares, M.L.D.	1980-1989	France	Palomares M.L.D.,Reyes-Marchant P.,Lair N.,Zainure M.,Barnabé G.,Lasserre G.(1993). A Trophic Model of a Mediterranean Lagoon, Etang de Thau, France . pp 224-229.

Few similarities exist between these ecosystems and studies, and no errors in methodology were found upon further examination. Therefore, it is assumed these studies and their data are legitimate and included for further analysis in this dissertation.

In an effort to simplify and increase the potential for explanation, replicability, and computing simplicity of applications elsewhere, we investigated the combinations of dropping not only the potential outliers identified in Table 4, but also the highly correlated variables found in Figure 6. To show the varying combinations more easily, it is useful to separate the metric combinations with varying degrees of positive or negative correlation into sets. The highly positively correlated metrics (≥ 0.8) will take the form:

$$P_1 = \left\{ \begin{matrix} Gen \\ Vul \\ LD \end{matrix} \right\}, P_2 = \left\{ \begin{matrix} C \\ C_{avg} \end{matrix} \right\}, P_3 = \left\{ \begin{matrix} HR \\ DR \end{matrix} \right\}, P_4 = \left\{ \begin{matrix} AC \\ RU \end{matrix} \right\}, P_5 = \left\{ \begin{matrix} FCI \\ APL \end{matrix} \right\}$$

Where each P_n value represents a highly positively correlated metric set from Figure 6. If we separate the highly negatively correlated metrics (≥ -0.8) into sets, we obtain:

$$N_1 = \left\{ \begin{matrix} AC \\ HR \\ DR \\ RU \\ APL \end{matrix} \right\}, N_2 = \left\{ \begin{matrix} C \\ C_{avg} \\ CE \end{matrix} \right\}$$

Where each N_n value represents a highly negatively correlated metric from Figure 6. If we continue with the remainder with metrics with lower degrees of correlation, we obtain:

$$A_1 = \{AMI\}$$

Where A_n is a size of one ($n=1$) with AMI being the only ecological metric with a low correlation with all other 13 metrics.

Examining the highly positive, highly negative, or less correlated sets above, we notice some of the positive sets (P_n) are subsets of the negative sets (N_n). In particular:

$$P_3, P_4 \subseteq N_1 \text{ and } P_2 \subseteq N_2$$

Therefore, if we exclude these subsets to remove repeated values, our highly positive, highly negative, and less correlated sets then become:

$$P_1 = \begin{Bmatrix} Gen \\ Vul \\ LD \end{Bmatrix}, P_5 = \begin{Bmatrix} FCI \\ APL \end{Bmatrix}, N_1 = \begin{Bmatrix} AC \\ HR \\ DR \\ RU \\ APL \end{Bmatrix}, N_2 = \begin{Bmatrix} C \\ C_{avg} \\ CE \end{Bmatrix}, \text{ and } A_1 = \{AMI\}$$

One may then notice Average Path Length (APL) is the only metric that repeats as shown in P_5 and N_1 . To calculate the number of possible combinations easily, it is best to have non-repeating values among sets. This leaves two options: (1) take the relative complement of N_1 in P_5 as a new set N_3 ($P_5 \setminus N_1$), which would be a set of size 1x1 and would replace P_5 alone or (2) create a new set P_6 that is the union of sets P_5 and N_1 ($P_5 \cup N_1$), which would result in a set of size 1x6 that would replace both N_1 and P_5 .

Choosing option 1 or 2 above has consequences in the amount of possible combinations of ecological metrics one may be faced with in our future PCA. From the multiplication principle, we know that by only using one value from each set, we multiply the number of items to get the total amount of possible combinations. Option 1 from above results in $(3 \times 1 \times 5 \times 3 \times 1 = 45)$ 45 different combinations while option 2 results in $(3 \times 2 \times 4 \times 3 \times 1 = 72)$ 72 different combinations. Therefore, we chose to proceed with option 1 resulting in the final metric sets as follows:

$$P_1 = \begin{Bmatrix} Gen \\ Vul \\ LD \end{Bmatrix}, P_6 = \{FCI\}, N_1 = \begin{Bmatrix} AC \\ HR \\ DR \\ RU \\ APL \end{Bmatrix}, N_2 = \begin{Bmatrix} C \\ C_{avg} \\ CE \end{Bmatrix}, \text{ and } A_1 = \{AMI\}$$

Our aim is to not oversimplify in this analysis and lose the data resolution required to accurately describe the emergent functionality of ecosystems derived from their high-level principles and properties. In our outlier detection, we observed the response of including and excluding ecological datasets and determined that including suggested outliers in our 100-ecosystem dataset did not impact correlation results in a substantial manner. We then explored the combinations of ENA metrics from the final metric sets above that best describe the variance of the data in the 100-ecosystem dataset using the minimum required ENA metrics in a PCA (e.g. one metric from each set). We determined the combination of LD, FCI, AC, C, and AMI best explain the variance of the data with the minimum required ecological metrics by running the 45 different combinations through the statistical software JMP and checking the cumulative percent of variance explained in the datasets.

Ecologists have studied these metrics (LD, FCI, AC, C, and AMI) applied to ecosystems extensively, describing emergent properties from analyzing groups of ecosystems that are healthy, in distress, and other heuristic traits. Connectance (C) and Linkage Density (LD) are both community-average descriptors of network structure only. This means they do not inform on the relative importance of each species to connectivity, but do provide useful information to infer some aspects of ecosystem performance (Landi, Minoarivelo, Brännström, Hui, & Dieckmann, 2018). For instance, C is a good estimate of community sensitivity to perturbation and LD can tell you if a random species is selected, how many interactions would it be expected to have (Berlow et al., 2004; Delmas et al., 2019; Dunne, Williams, & Martinez, 2002). Linkage Density seems to form a pattern around the energy flow from resources to consumers and a key feature for food web topology (Scotti, Bondavalli, & Bodini, 2009). However, some literature suggests LD should be used with caution, as the distribution of interactions among species in networks is shown to be rarely uniform or normal (Williams, 2011).

Similarly, Average Mutual Information (AMI), Finn Cycling Index (FCI), and Extent of Development (AC) are flow-based measures that all have emergent properties. FCI is said to be a measure of ecosystem maturity (E. P. Odum, 1969), AC directly measures ecosystem development as compared to the theoretical maximum in a measure of system efficiency. AMI This is the degree of specialization in the system or the number of constraints on the materials and/or energy flow and is known to be indicative of developmental status (Bodini & Bondavalli, 2002).

Figure 8 below shows the correlation of the pared-down ecological metrics after excluding the outliers.

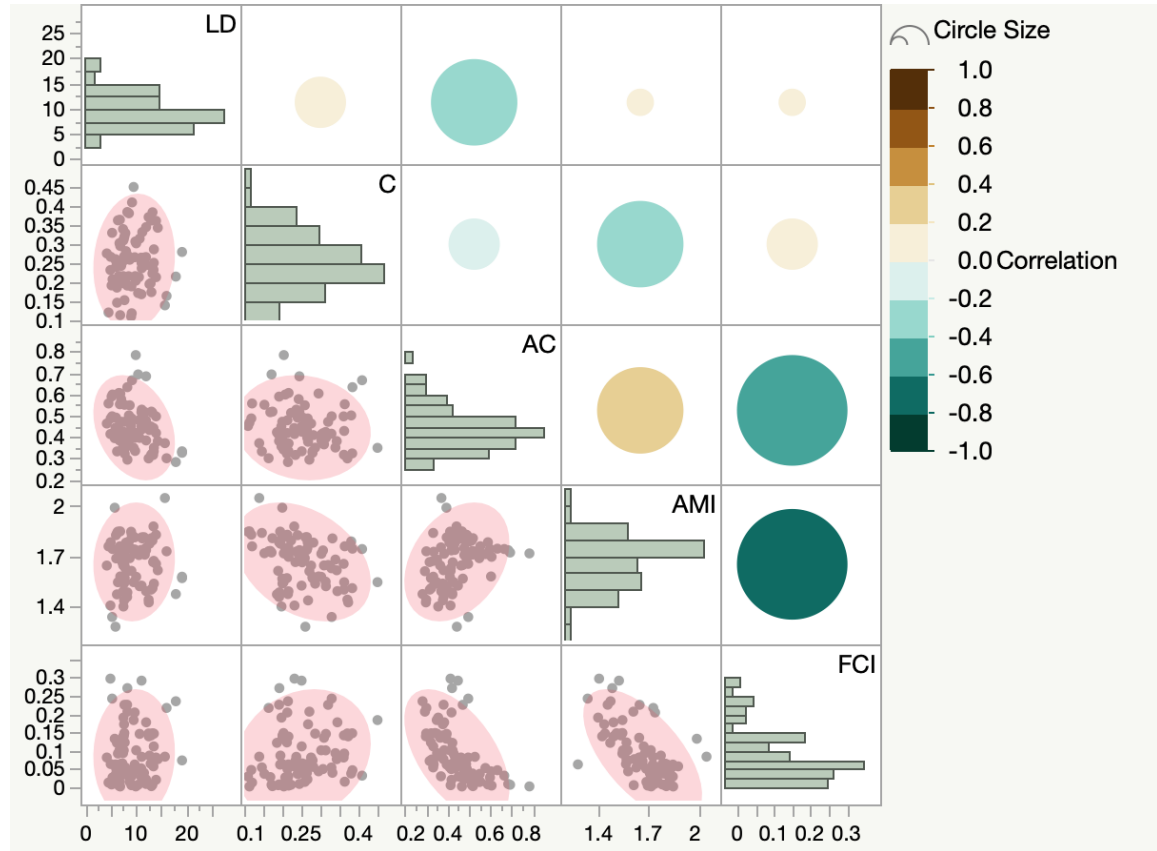


Figure 8. Correlation Plot After Exclusion of Outliers. The Rows and Columns Titles are Labeled Across the Diagonal.

As one may observe, after the exclusion of the outliers, the correlation between AMI and FCI increased slightly (0.6-0.8 in comparison to 0.4-0.6 in Figure 6) and the Mahalanobis distance found more outliers with an decreased UCL of 3.268 (down from 3.28) shown below in Figure 9.

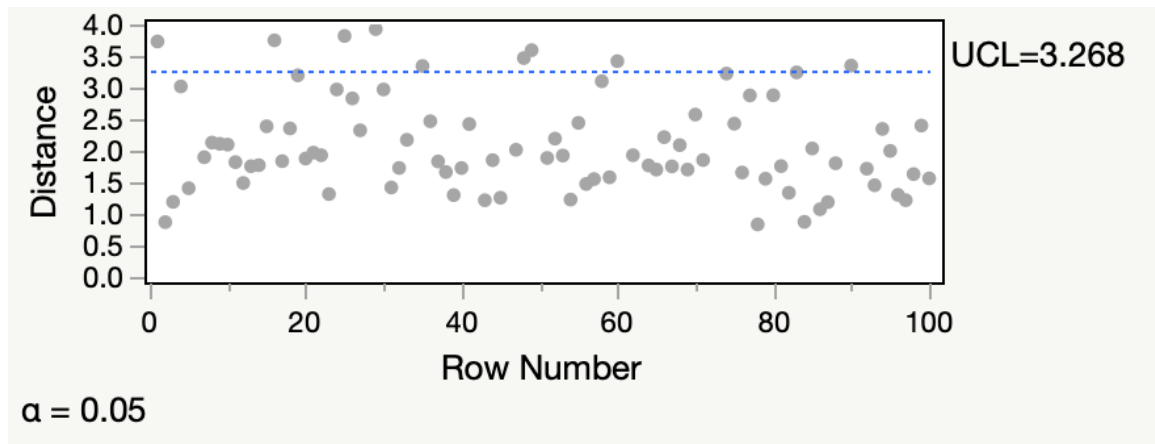


Figure 9. Mahalanobis Distance After Exclusion of Outliers

These results suggest that the exclusion of the outliers did not have a large effect on the correlation results. To confirm this, we then included the outliers and re-analyzed the correlations as shown below in Figure 10.

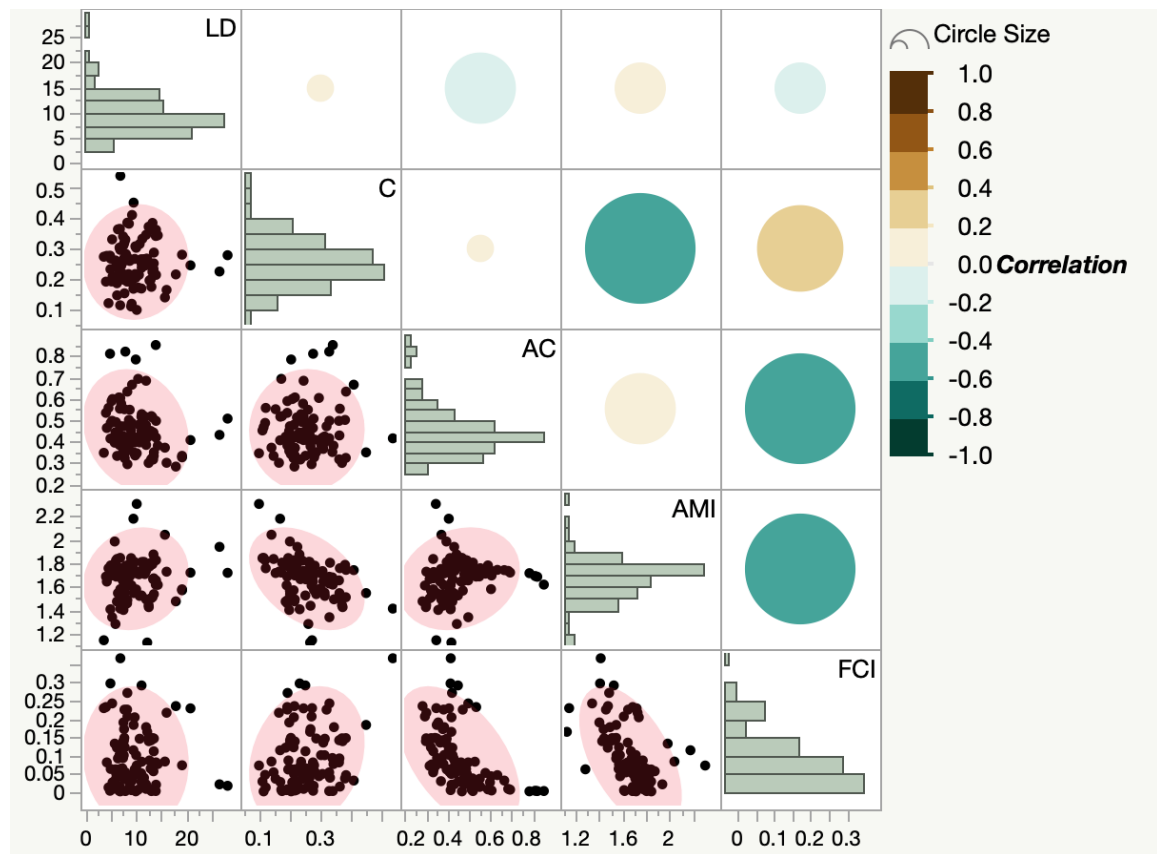


Figure 10. Correlation Analysis Without Outlier Exclusion. The Rows and Columns Titles are Labeled Across the Diagonal.

The plot shows that the data is less correlated than with outliers excluded with a (~0.012 decrease) on the UCL in the Mahalanobis plot in Figure 9. Researchers have found that the lack of correlation amongst variables leads to a better representation of the covariance in the data when the Principle Component Analysis is conducted in the following section (Lever, Krzywinski, & Altman, 2017). As such, of the 100 ecosystems originally analyzed, it was concluded that none should be excluded from our analysis as it was determined their exclusion may skew the results of the ensuing Principle Component Analysis. Therefore, Linkage Density, Connectance, Extent of Development, AMI, and

FCI were the metrics chosen from this correlation analysis that best represent the ecosystem dataset with the minimum number of variables.

The individual histograms and simple statistics are displayed below in Figure 11.

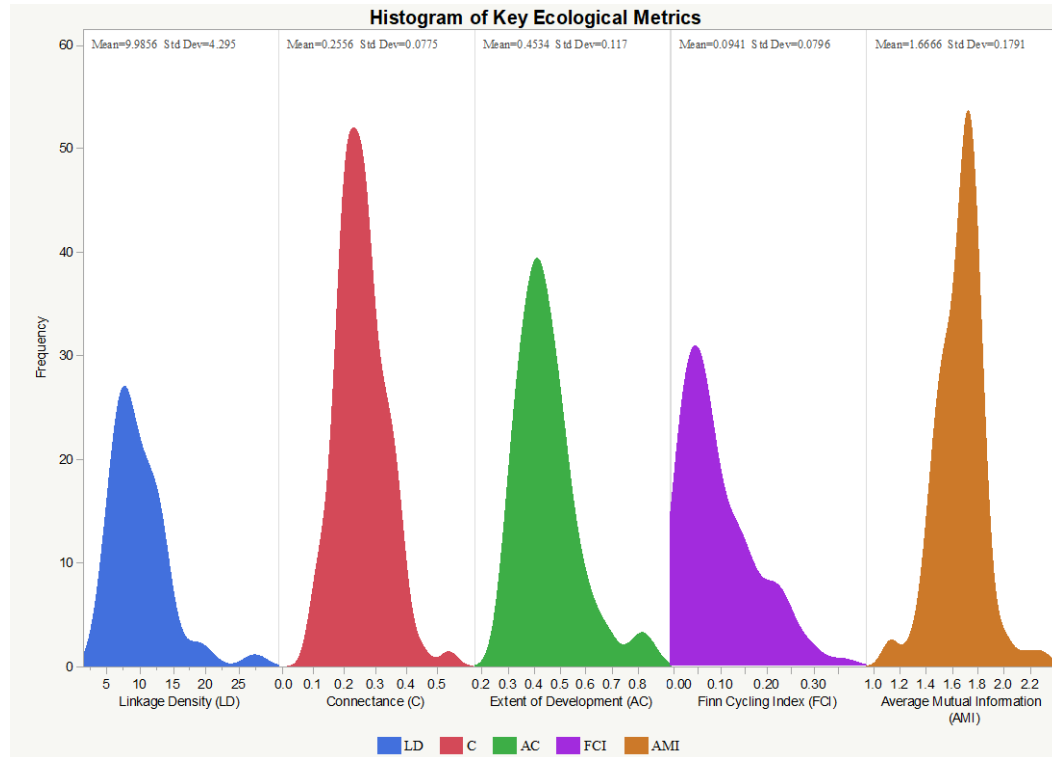


Figure 11. Histogram and Simple Statistics of Key Ecological Metrics


These statistics show 9.99, 0.26, 0.45, 0.09, and 1.67 for LD, C, AC, FCI, and AMI respectively. Of these averages, LD has the highest standard deviation with 4.30 while the other metrics show standard deviations less than 0.18.

3.3.3 Principle Component Analysis of Food Web Metrics

Principal Component Analysis (PCA) simplifies the complexity in high-dimensional data while retaining trends and patterns by transforming the data into fewer dimensions, called principal components, which act as summaries of features (Lever,

Krzywinski, & Altman, 2017). These principle components act as a linear combination of the data's original variables (FCI, LD, etc.) that explain the highest amount of covariance in the data. We used the multivariate tools from JMP Pro version 15 with the 100 ecosystems introduced previously and the ecological metrics LD, C, AC, AMI, and FCI shown in the diagonal of Figure 10.. Table 5 below shows the results of the principle component analysis conducted on these ecological metrics.

Table 5. PCA Cumulative Percent of Variance Explained

Number	Eigenvalue	Percent		Cum Percent
1	2.0550	41.100		41.100
2	1.2254	24.508		65.608
3	0.7403	14.806		80.414
4	0.6342	12.684		93.098
5	0.3451	6.902		100.000

The results demonstrate that 65.6% of the variance in the data is explained by the first two principle components. According to Cangelosi and Goriely (2007), there is no minimum on the variance explained by the data, but cumulative percent should not be relied on independently. A scree plot, loading plot, partial contribution of variables, and other methods should bolster the analysis and determine the number of components used in an analysis result.

Figure 12 below shows a loading plot that shows the contribution of the variables across the two primary principle components.

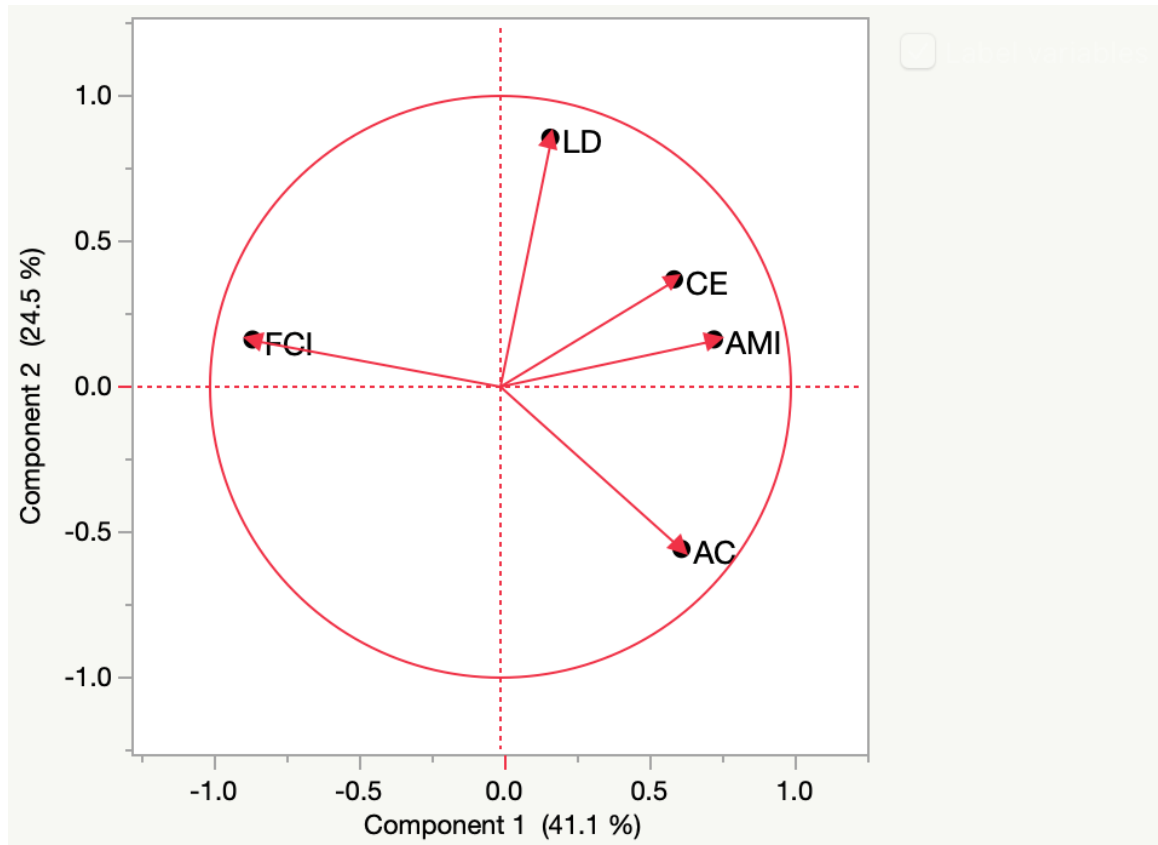


Figure 12. Loading Plot of Metric Impact Among Components

As one may observe from Figure 12, the majority of the metrics (AMI, CE, LD) have a positive and relatively equal loading with respect to the first and second principle component. FCI is shown to have a positive loading with respect to the second principle component but a negative loading with respect to the first principle component. AC is shown to have a positive loading to the first principle component but a negative loading with respect to the second principle component. All metrics show a similar loading strength, with CE showing a slightly less loading strength as compared to the other metrics.

Another way to look at the loading plot is by visualizing where the projected data points from the PCA lie with respect to the loading plot and the principle components. Figure 13 below shows the data points and loading plot.

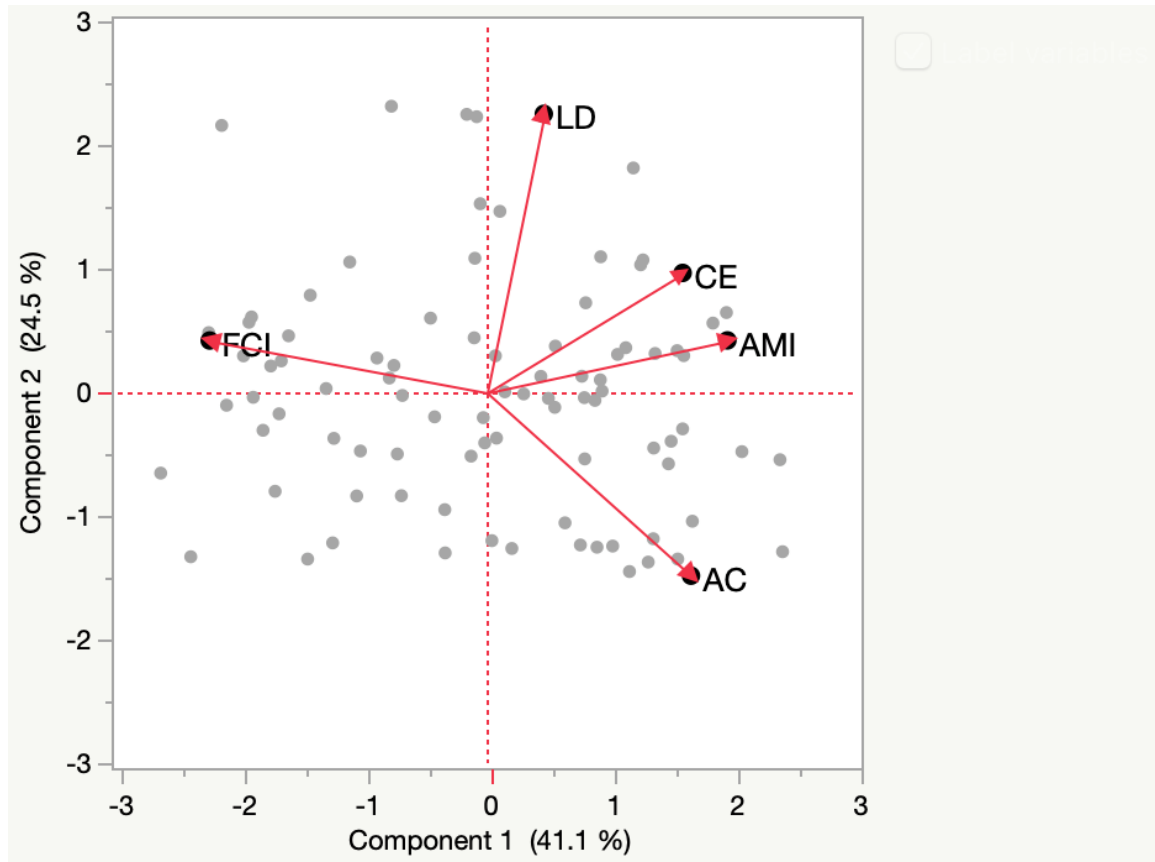


Figure 13. Biplot of Metric Loading Among the First Two Components

As one may observe, the biplot shows that there is a large amount of variance explained by the FCI and AC metric, where the LD, CE, and AMI all explain a large portion of densely clustered points. This provides confidence that the pairing down of the metrics to FCI, LD, CE, AMI and AC did not leave a large majority of the variance in the first two principle components unaddressed.

The scree plot can be useful to determine the number of principle components to retain in a PCA. The plots show the eigenvalues in a downward curve, ordering the eigenvalues from greatest to least. Figure 14 demonstrates the scree plot for our PCA.

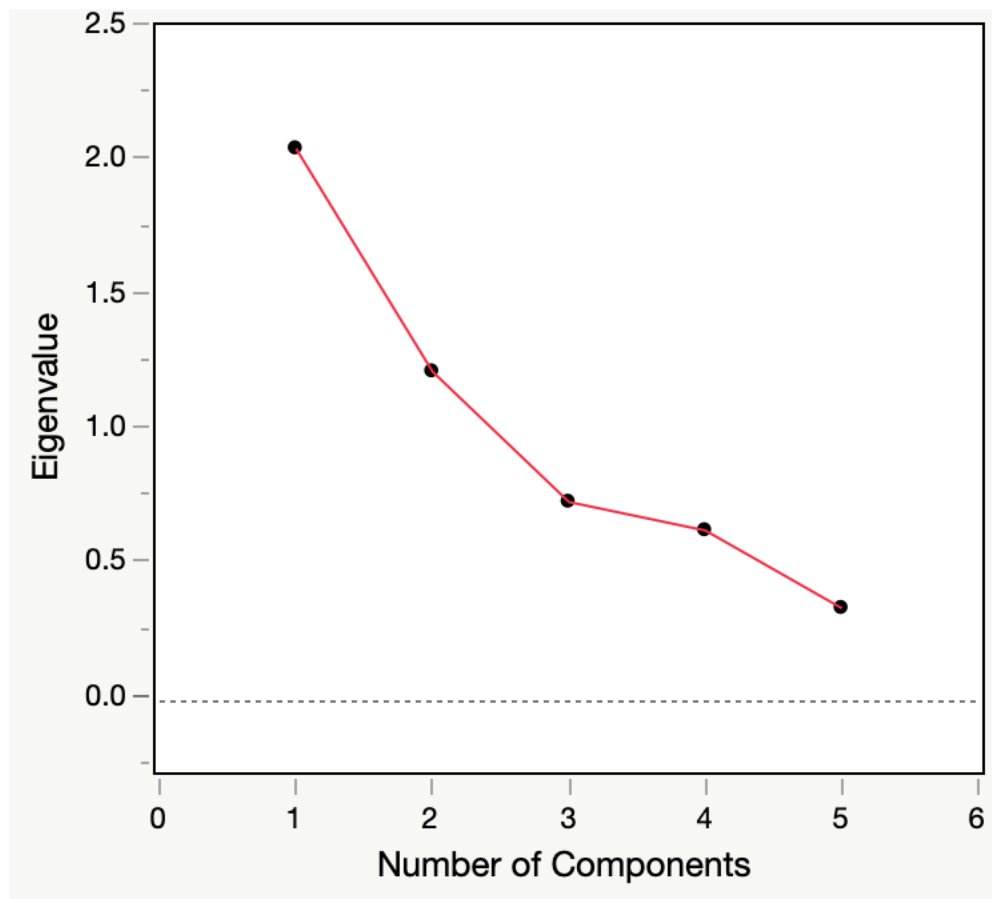


Figure 14. Scree Plot of Eigenvalue per Number of Components

Typically, in a scree plot the elbow of the graph, or the eigenvalues before where the “levelling off” occurs, are the values one would retain for their analysis and deemed significant. In this case, one can observe that the plots “elbow” may be around the 3-components mark. However, it could also be argued that the elbow occurs earlier as well, bringing about subjectivity in our analysis. This is often a point of criticism for the scree plot test (Streiner, 1998), and it is understood the reduction of components would lead to higher interpretability but lower accuracy. Therefore, in our analysis we will seek to have a more well-rounded case for retaining principle components rather than relying on the scree plot alone.

One method for providing a more well-rounded case is looking at the partial contributions of variables in the PCA. Figure 15 below shows the partial contributions among the first three principle components.

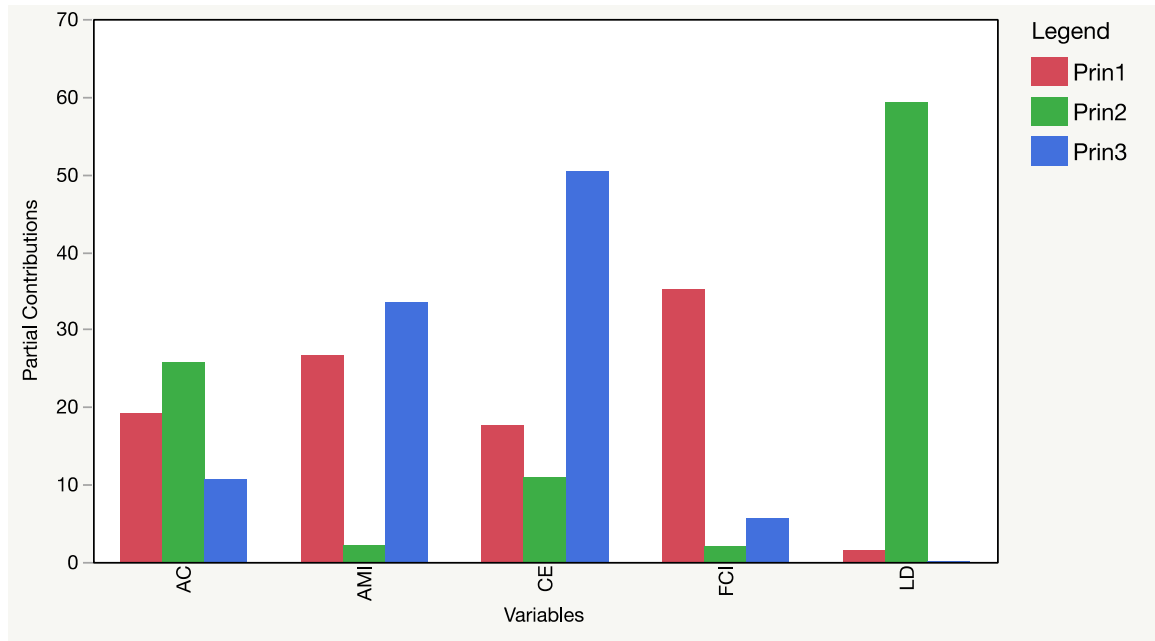


Figure 15. Partial Contribution of Variables in PCA Analysis

As one may observe, the first principle component is spread relatively evenly throughout the variables AC, AMI, CE, and FCI. The second principle component is primarily represented by LD and AC. The third principle component is again spread across the same variables as the first component (AC, AMI, CE, and FCI). Due to this, we can conclude that the first component and third component explain a similar proportion of the variance among similar variables, and thus the one explaining the lesser amount may be excluded from analysis. Additionally, the second principle component primarily attributes its partial contribution to the LD variable, where the third principle component explains none of the variance in this variable. As such, we have determined that the third principle component may be excluded in our analysis without skewing the results from our PCA or limiting our goal of identifying key ENA metrics for ecosystem functionality.

3.3.4 Cluster Analysis of Food Web Metrics

Variable clustering provides a means to group similar variables into representative groups. This method is effective in understanding the structure of a data set but may also be used to reduce the number of variables without sacrificing too much information. Variable clustering is achieved by dividing a set of observations (in this dissertation, ecosystem metrics) into groups or clusters in a way that most of the members of the cluster are similar to each other. Typically, little or nothing is known a priori about the groups and the objective is to divide the given observations into groups or clusters in a ‘sensible’ way (Jolliffe, 2002). This ‘sensible’ clustering is defined as a measure of similarity or dissimilarity between two pairs of observations, and principle components have been used to express dissimilarity as the Euclidean distance between observations in the p-dimensional space defined by the variables.

The variable identified to be the most representative member represents the cluster. One method of identifying this most representative member is achieved through an algorithm originally developed by SAS and is implemented in the VARCLUS procedure (SAS Institute Inc., 2018). The clustering algorithm iteratively splits clusters of variables and reassigns variables to clusters until no more splits are possible, and the initial cluster consists of all variables. This Table 6 shows the results from the Cluster Analysis in JMP Pro 15 with the five ecosystem metrics FCI, AMI, AC, CE, and LD.

Table 6. Cluster Summary

Cluster	Number of Members	Most Representative Variable	Cluster Proportion of Variation Explained	Total Proportion of Variation Explained	
1	4	FCI	0.51	0.408	
2	1	LD	1	0.2	

As shown, the algorithm found two clusters where the most representative variable is FCI in the first cluster, and LD in the second cluster. Table 7 breaks down in more detail the exact contributions of the metrics to the two clusters.

Table 7. Cluster Members

Cluster	Members	RSquare with Own Cluster	RSquare with Next Closest	1-RSquare Ratio
1	FCI	0.733	0.005	0.268
1	AMI	0.533	0.019	0.476
1	AC	0.44	0.031	0.578
1	CE	0.335	0.051	0.701
2	LD	1	0.007	0

Cluster 1 is comprised of FCI, AMI, AC, and CE. FCI has the highest correlation with cluster 1. Cluster 2 is solely comprised of LD and is thus the metric with the highest correlation in its cluster. Of both clusters, one can observe that 61% of the variance can be explained by the two metrics FCI and LD, with FCI providing the majority of the contribution (41%) compared to LD (20%).

3.4 Discussion of PCA and Cluster Analysis

The results from our PCA and cluster analysis indicate that the ecological metrics Finn Cycling Index (FCI) and Linkage Density (LD) best explain the majority of the variance in our 100-ecosystem dataset. We interpret this as if one was to choose two metrics of the original 24 ENA metrics introduced in Section 2.3.2 that are most essential to describe ecosystem functions, FCI and LD would be the best choices. Furthermore, if engineered systems were to achieve levels similar to those demonstrated by ecosystem values of FCI and LD, then these engineered systems would be progressing towards the structural and flow-based configurations found in ecosystems.

We believe this is a convenient finding from an engineered systems design perspective, as one metric (LD) is a structural measure while the other (FCI) is flow-based measure. FCI has been shown previously to be unique when compared to existing flow cycling measures used in industry, therefore its use in the design of engineered systems would be both novel and useful (Bailey, 2000). However, past work has also shown that the structural configuration is very important to the holistic design and performance of engineered systems using ENA, so the inclusion of LD along with FCI is favorable (Astrid Layton, 2016; Astrid Layton, Bert Bras, & Marc Weissburg, 2016a; Reap, 2009). Some ecologists have also concluded FCI (among 7 other metrics) has potential for providing high level information for environmental decision-makers and stakeholders on ecosystem status, suggesting a rendezvous at a similar conclusion by different methods. However, these past results have been less targeted and often include an array of structural and flow-based measures and literature has shown that the economic costs associated with the development and explanation of an engineered systems model is directly related to its complexity and accuracy. (Jones, Schonlau, & Welch, 1998; Roy, Souchoroukov, & Shehab, 2011). Therefore, we suggest a more targeted approach using the ENA metrics LD and FCI would lead to enhanced adoption of ENA for engineered systems design by both economic incentives and ease of translation of the scientific merit to industry stakeholders. This targeted approach would benefit areas such as multi-objective optimization in engineering design. For designs that do not require optimization, the expanded five-metrics (LD, FCI, AC, CE, and AMI) could be introduced without requiring much more complexity in the analysis.

This use of PCA applied to ENA metrics has not been performed previously by ecologists due to the high correlation amongst the common metrics. However, literature suggests some ecologists use PCA to explain ecosystem dynamics over time alongside ENA metric calculations (Tomeczak et al., 2013). In our analysis, we took the liberty of pairing down the common ecological metrics to side-step any issues associated with highly correlated ENA metrics in a PCA. This approach introduces some obvious limitations with our current results, but also offers some opportunities for future work.

A choice bias is introduced as a limitation in our analysis by pairing down the common ecosystem metrics introduced in Section 2.3.2 based on their correlations. We excluded metrics of correlations below the brackets of Pearson correlation coefficient highly positively/negatively values of $[\pm 0.8:\pm 1]$. We know from simple statistics that the value of this correlation coefficient indicates the strength and direction (positive/negative) of the linear relationship between two continuous variables. However, the strength of the relationship as defined in this study excludes those metrics with weaker correlation coefficients that still suggest a moderate relationship (i.e. a value of ± 0.6). There is not a one-size fits all answer of where to draw this line, and if this analysis were to include values with weaker correlations it would most definitely affect this study's results and possibly the overall conclusions. However, to overcome paralysis by analysis and move forward, the scope of this study did not include this exploration. Therefore, it is recommended that future work should investigate this possibility to further support the results of our work.

3.5 In Closing

This chapter is devoted to attempting to understand the intricacies of ecosystem metrics and how they compare to one another in context to a large dataset of aquatic ecosystems. In summary, this chapter sought to understand the following questions:

- Which metrics can be excluded due to their high level of correlations?
- Which combination(s) of the remaining metrics best explain the variance in the ecosystem datasets?

As it turns out, these questions are more complicated than they seem. However, though this PCA we have shown that several metrics remain once a list of metrics is filtered to the variables that are either highly positively or negatively correlated with other metrics. AC, AMI, CE, FCI, and LD are five of the remaining ecosystem statistics of the original thirteen that we examined at the onset of this multivariate analysis. Therefore, we now understand that these five metrics are key to representing ecosystem functionality (as explained by the variance of the data) and with PCA we have shown that these variables in the form of principle components explain a high level of variance among our ecosystem dataset. This also brings about the question – is there any one of these metrics that can be noted as being the most representative variable amongst the group?

Through clustering analysis, we have determined FCI to be that variable, and will be a key variable of interest moving forward to case studies in later chapters. In addition, LD seems to be the next leading variable found in our clustering analysis. If one refers back to Table 3, one may observe that LD is a member of the “general indices” network measure, and FCI is a member of the “pathway analysis” network measure. These metrics may be

the key indicators of a “balance” in the network structure and the flows through a network from the graph and information theory perspective and may be the guiding light in its application to engineered systems design.

CHAPTER 4. THE APPLICATION OF DETRITAL ACTORS IN ENGINEERED SYSTEMS

In the previous chapter, we found that Finn Cycling Index and Linkage Density were the two ecological metrics from Ecological Network Analysis that explained much of the data variance amongst an analysis of 100 ecosystems. This understanding then leads to the question, how might one design engineered systems from conception or retrofit currently existing systems to increase these ecological metrics and decrease the performance gap between natural and engineered systems? In this chapter, we explore how natural systems achieve their levels of material and energy efficiency and how these lessons may be translated to engineered system design.

4.1 Research Tasks and Goals

The following section contributes to the completion of Research Task 2 and Research Task 3 by delivering a classified and categorized collection of technological, biological, or hybrid systems. This in turn will facilitate the completion of Research Goal 1.5.2.

4.2 Background & Motivation: The Decomposer Functional Role

Natural ecosystems are limited by the resources available in their environment and, as with all systems, are governed by the laws of thermodynamics (S. Nielsen, Müller, Marques, Bastianoni, & Jørgensen, 2020). This means the availability of these material or energy resources may be attributed to a variety of factors including climate, geographic

location, and impact due to human interference. As such, ecosystems have adapted through periods of material and energy shortage to efficient and robust configurations.

As presented in Figure 3 of the Introduction, the individual species in ecosystems may be divided into specific functional roles and levels such as producers, consumers, and decomposers. Ecologists have shown that the inclusion of the decomposer functional role is integral to ecosystem functionality; as the decomposer functional role allows for additional energy in the system to be available, which impacts the overall biodiversity, food web structure, and transient responses. Additionally, some studies have shown this decomposer functional role can be involved with over half of the material flows within an ecosystem (Carrer & Opitz, 1999).

These decomposers and detritivores (i.e. detrital feeders) that make up this decomposer functional role accomplish this by converting dead organic matter and waste from all trophic levels into inorganic nutrients that fertilize the growth of the producers (Bergon et al., 1986; Freedman, 1998). Both decomposers and detritivores are lumped together in this dissertation as they are functionally related for our purposes. These decomposers typically consist of, but not limited to, an array of bacteria and fungi that absorb and metabolize the material flows in natural systems. Decomposers break complex organic tissue into the fundamental components of carbon dioxide, water, and inorganic nutrients that can then be re-introduced as food to the higher trophic level consumers in the ecosystem (Carrer & Opitz, 1999). In addition, decomposers are often biochemically specialized to consume organic materials and waste products that are difficult for other organisms to digest (Geng & Côté, 2002).

Previous research has shown these decomposing systems lacking or missing altogether when engineered systems are analyzed through an ecological lens (Astrid Layton et al., 2017; S. M. Malone, Cohen, Bras, & Weissburg, 2018). Through discussions with industry professionals, we have found that Engineers are typically tasked (sometimes over-tasked) with designing energy systems or material and water systems, or both simultaneously. This leads to a heavy reliance on run-of-the-mill designs from past experiences with little modifications resulting in slow innovation cycles (Foran, 2019).

To implement these decomposing systems in a design today requires both intensive research and time; rare commodities in the design realm. Therefore, the motivation of this chapter is to lay the groundwork for creating a collection of these “decomposers” matched to individual waste streams. This will create a bridge to implementation in the design community and provide expansion to current academic undertakings in both the fields of Industrial Ecology and Circular Economy.

4.3 Methods: From Theory to Implementation

The application of the decomposer functional role as a means of eliciting material exchange requires detailed data at the company level in order to classify, categorize, and match waste flows between industries (P.-C. Chen & Ma, 2015). However, discovery of and classification of industrial waste data can be difficult to achieve. This is either by design (e.g. confidentiality, trade secrets, etc.) or because it is time-consuming to collect (Bremner, 2012; Patricio, Kalmykova, & Rosado, 2020). A top-down approach, whereby industries are classified according to broad waste types, has proven useful towards sustainable material management (Krones, 2016). In this section, we provide a

methodology that builds on previous studies that utilize the structure of the North American Industry Classification System (NAICS) database.

4.3.1 Characterization and Classification of Common Waste Streams

In this thesis, the waste streams found in industry are of upmost importance to apply the translative insight from, and rise to the material and energy performance of, those found in ecosystems. An important step in realizing this potential is connecting waste generating streams in these industries with others that consume the same waste streams. Therefore, a characterization and classification schema are needed, and several researchers have worked to address this need (S. M. Malone et al., 2018; Raleigh, Knox, & Canter, 1995).

A promising body of work is from Raleigh et al. (1995) that uses the North American Industry Classification System (NAICS) to connect industries with similar waste streams. Table 8 below shows the NAICS industrial code classification scheme.

Table 8. NAICS Industrial Codes

Code	Classification	NAICS Industrial Code
A	Agriculture, Forestry, Fishing, and Hunting	11
B	Mining, Quarrying, and Oil and Gas Extraction	21
C	Energy Utilities (Electric Power Generation, Transmission and Distribution)	2211
D	Water Utilities (Water, Sewage, and Other Systems)	2213
E	Construction	22
F	Food Manufacturing	311
G	Textile Mills and Textile Product Mills	313/314
H	Wood Product Manufacturing	321
I	Paper Manufacturing	322
J	Petroleum and Coal Product Manufacturing	324
K	Chemical Manufacturing	325
L	Plastic and Rubber Product Manufacturing	326
M	Non-metallic Mineral Product Manufacturing	327
N	Primary Metal Manufacturing	331
O	Computer and Electronic/Electrical Equipment Manufacturing	334/335
P	Transportation Equipment Manufacturing	336
Q	Furniture and Related Product Manufacturing	337
R	Waste Industries (Collection, Treatment/Disposal, Remediation, and Other Management Services)	562
S	Other Industries	

Raleigh et al. (1995) shows this classification scheme from Table 8 may then be expanded to specific waste categories, which then can be matched to the specific NAICS classification code, as demonstrated below in Table 9.

Table 9. Waste Stream Categorization and Classification Matching Using the NAICS standard

Waste Stream	Waste Category	From Classification Code	To Classification Code
Spent Solvents	Chemical	C,D,F,I,J,K,N,O,R	B,C,D,F,I,J,K,L,M,N,O,R
Residual Acids/Alkali			
Sulfur			
Industrial Gases (CO ₂ , H ₂)			
Activated Carbon			
Spent Catalyst			
Metal Scraps (Iron, Steel, Copper, Lead, Zinc)	Metallic	I,N,O,P,R	D,K,M,N,R
Slag (Blast Furnace, Steel, Lead)			
Solder Materials			
Bauxite Residue			
Spent Lead Acid Batteries			
Fly Ash	Ash	C,I,R	A,B,E,K,M,R,S

Table 9. (Continued)

Bottom Ash			
Mixed Ash			
Burnt Residue			
Food Waste	Organic	A,F,K,N,R,S	A,C,F,I,K,M,R,S
Biomass			
Fertilizer			
Other Organic Waste			
Sewage Sludge	Sludge	D,F,I,J,M,N,P,R	A,B,C,D,K,M,R
Refinery Sludge			
Paper Sludge			
Fiber Muds			
Filter Cakes			
Cardboard	Paper and Wood	H,I,M,Q,R,S	A,H,I,M,S
Mixed Paper			
Wood Dust			
Wood Chips			
Wood Trimmings			
Synthetic Gypsum	Non-Metallic	B,C,K,M,O,R	E,M,N
Construction and Concrete Waste			
Glass Scrap			
Coal Mine Overburden			
Lime Kiln Dust			
Silica Fume			
Polystyrene	Plastics and Rubber	F,I,L,R	J,L,M,N,R,S
Waste Plastics			
Off-spec Plastics			
Rubber Scrap			
Used Oil from Chemical Processes	Oil	F,K,R	J,K,M
Edible Oil from Food Manufacturing			
Textile Waste	Other	D,G,I,J,R	J,M
Fine Materials			
Biogas			
Excess Gas			

These classification and categorization schemes are an important first step in realizing the objectives of this chapter and are only one of many potential frameworks (Bakshi, 2002;

Bakshi & Fiksel, 2003; Wilson & Rosen). The initial scaffolding shown in Table 9 provides a robust platform to build upon. However, there are several suggestions for improvement that we explore to refine and build upon the work of Raleigh et al. (1995).

In particular, we refine the waste streams further to be more accurate. We also add to the current waste stream list to include other wastes not yet considered such as drilling fluids or energy recovery in the form of heat. We also expand the current approach by adding classified biological, technological, or hybrid material and energy “decomposers” that upcycle waste streams into value-added products. Further, we provide parametric equations for these “decomposers” that help designers accurately size and estimate costs associated with their use. Finally, we add limitations or criteria for implementation for these decomposers with associated literature sources so that others may pursue their own calculations or check the validity of others’ findings.

The hope is that this effort will allow for the discovery of engineered systems options and opportunities that designers are not currently aware to help facilitate the design more sustainable systems. This knowledge base will further the already established efforts in the research community and seek to address some of the issue’s designers face. It will also demonstrate how this classification and characterization scheme may be utilized and expanded upon to generate a database.

4.3.2 Expansion of the Waste Stream Characterization and Classification Schema

The expansion of the classification and categorization schema introduced by Raleigh et al. (1995) in this work can be summarized in three steps shown below in Figure 16.

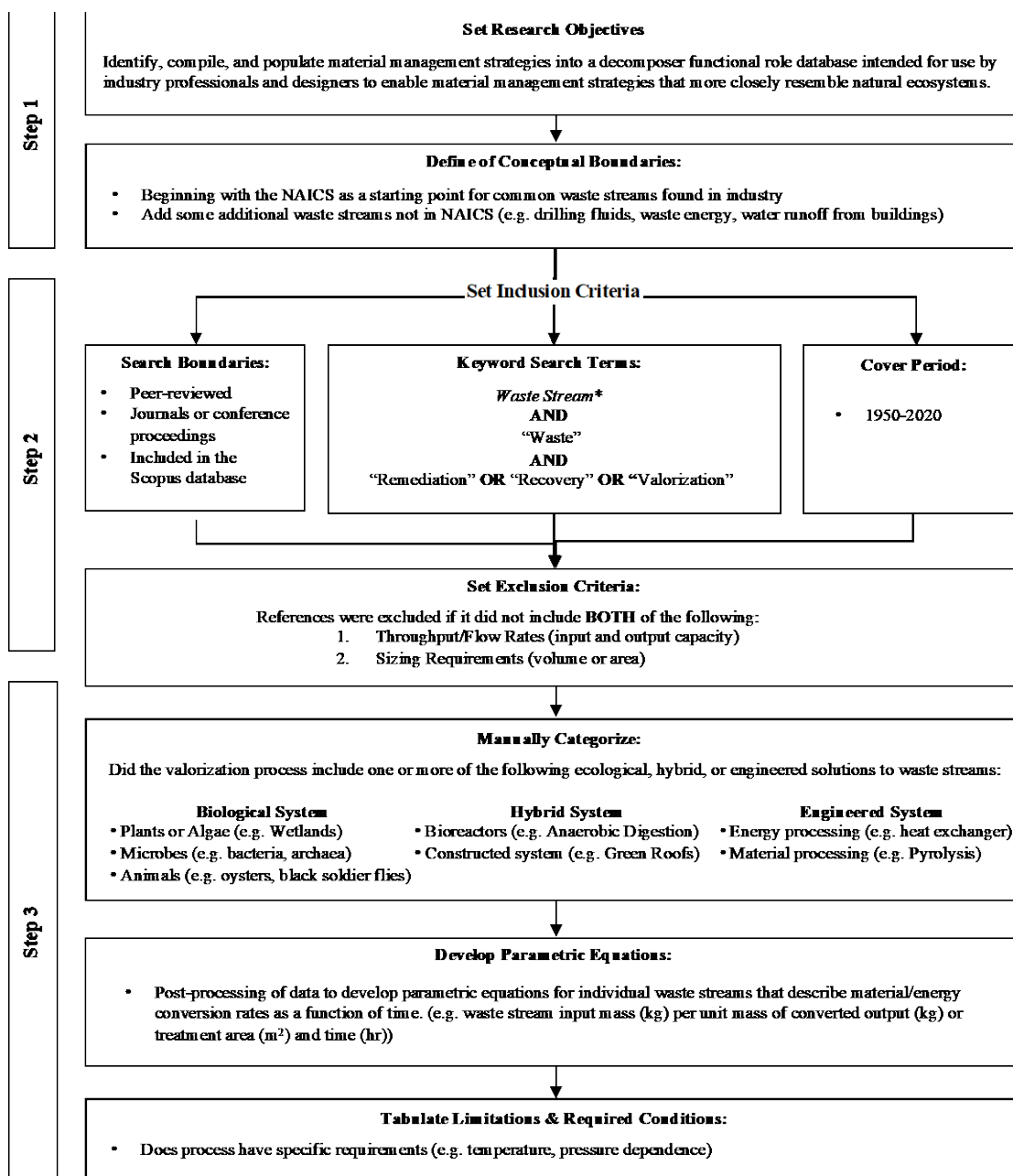


Figure 16. Steps to Generate Biological, Technological, or Hybrid Decomposers

The first step was to include several waste streams not included with the original NAICS database and include them under existing or the "Other" categories shown in Table 9. These included drilling fluids (especially relevant with the prevalence of hydraulic fracturing for natural gas extraction in the United States), an air pollutants category, an

energy recovery category, and water runoff recovery. Energy recovery, air quality, and water runoff recovery are becoming increasingly important topics in the green building communities as more and more customers are pushing for designs that are close to, or achieving, net zero energy consumption (Foran, 2019). Water and energy recovery were not considered as potential waste streams in the work proposed by Raleigh et al. (1995). However, it is the belief of the author that these types of recovery systems must be considered as they are integral to efficient resource utilization in both high performing engineered systems and ecosystems.

The refinement of the current waste streams shown in the first column of Table 9 into more specific waste streams is accomplished in the second step in Figure 16. This second step expands the current classification and characterization schema from Raleigh et al. (1995) by introducing a higher resolution to the individual waste streams. For instance, the waste stream metal scraps from Raleigh et al. (1995) includes all types of metal scraps, for which there are several primary (steel, aluminum, lead, etc.) contributors. These must be broken down further, as not every facility in the industries provided in the classification schema can accept all of these metals. For example, a steel industry could find value in receiving scrap steel to supplement their manufacturing process, however receiving lead would be far less useful to their efforts. Another example is the industrial gasses waste stream in Table 9 that includes all industrial gasses, for which there are hundreds if not thousands of compositions. There are several levels of refinement of this waste stream of gasses in industry that could provide more precise and useful information needed to accurately map these gasses to industries that need them.

The goal of this chapter is to determine the “decomposers” that can be matched to these individual waste streams. We began by a literature search in peer-reviewed journals or conferences proceedings in the Scopus database by using the keyword search terms: Waste Stream* AND “Waste” AND “Remediation” OR “Recovery” OR “Valorization” for the cover period 1950-2020. The Waste Stream* entry is replaced by the individual waste from Table 9. The cover period is to keep with the most up to date information and the past 60 years should provide enough depth for this goal. Peer-reviewed journals took priority over conference proceedings to maximize the quality of data.

The results from these searches provided many academic sources that needed to be filtered for relevancy. The results from the Scopus search were analyzed and excluded unless the entry had the following information: Both throughput/flowrates in the study per unit time and sizing information (volume or area). These exclusion criteria requirements will allow designers to have access to the relevant information for modeling their inclusion in engineering designs and also with modeling approaches such as ENA. The most sought-after studies in the Scopus search will also include some cost estimation, as these will allow for designers to justify their decisions with respect to the study’s economic impacts.

The third and final step in the expansion of the classification and categorization schema introduced by Raleigh et al. (1995) and shown in Figure 16 is to add a categorization based upon whether the “decomposer” is a biological, technological, or hybrid solution to a waste stream. In this work, biological solutions take priority over technological or hybrid solutions, as the study of technological systems in the engineering community is extensive or are entire research fields altogether. However, the incorporation

of biological systems in engineering design is a field in its infancy and not well established - therefore there is a need of a systematic transfer of natural systems insight to the engineered world (Wilson & Rosen). By categorizing “decomposer” solutions and focusing on those that rely on biological processes, we are addressing this need by proving a means of easy adoption that is familiar to engineered system designers and researchers alike.

This familiar means of adoption in this study relies on the concept of a parametric equations that represent material or energy transformation functions with respect to the independent variable time. These types of equations are taught to most undergraduate students in Science, Technology, Engineering, and Mathematics (STEM) fields to model the transient response of systems such as those found in kinematics or computer-aided design. By representing the information in the studies of our Scopus search in this manner, a familiar transformation of biological systems capabilities may be transferred to an engineered systems application. The units of the entries are represented as the mass/energy of waste stream per unit of converted output or treatment area and time.

This type of equation is inherently a simplification of most study results from our Scopus search, and therefore will have certain limitations, assumptions, or required conditions to remain valid. Some of these may be temperature or pressure dependence, or other operational requirements such as time of year or specific mechanical equipment. As such, these limitations and required conditions are specified in conjunction with the parametric equations. These limitations and required conditions are not meant to be comprehensive to all situations, but enough for a high-level estimate. A more in-depth

discussion of feasibility is presented in Section 4.4.1 below. Further, if any type of post-processing is required (such as methane refinement for co-digestion for use in power production), there is a column that provides a Boolean value of true or false. Finally, the source of the study used to generate the parametric equation is presented to allow for validation and quality checks of the parametric equations and to provide further details of the study that may relate to the operational parameters, costs, or other important details.

4.3.2.1 An Example Parametric Equation Calculation with a Biological Intervention: Plants to Uptake Chloride in Wastewater

This example stems from the idea of some plants being better than others at removing contaminants from soil or water in a process known as phytoremediation. In searching literature, a study was found that incorporates the plants *J. torreyi* and *T. latifolia* in a constructed wetland to uptake the contaminants Na^+ and Cl^- in water (E. R. Rozema, R. J. Gordon, & Y. Zheng, 2016). Chloride can foul mechanical equipment in water systems, so this would be a specific waste stream to remove from water systems in an engineered system. Traditionally, this would be accomplished with an energy intensive reverse osmosis process in a water treatment facility. However, similar results may be achieved through the use of a constructed wetland.

Determining the Treatment Rate

The relevant information in the study is spread throughout the paper that is necessary to create our parametric equation. The first is from Table 1 of Eric R. Rozema et al. (2016) where three scenarios are introduced for each plant species (JT-1, JT-2, JT-3, TL-1, TL-2, TL-3). Our goal is to remove chloride, so the two scenarios chosen

for *J. torreyi* and *T. latifolia* are JT-2 and TL-3, respectively that yield both the highest chloride uptake per square meter (g m^{-2}) as shown in Figure 3 of the Rozema's study. Using this information, along with the total experiment length (18 weeks or 126 days), we were able to calculate the chloride rate per unit area ($\text{mg Cl}^{-} \text{d}^{-1} \text{m}^{-2}$). Altogether, this can be shown below in Table 10:

Table 10. Relevant Information for Parametric Equation from Eric R. Rozema et al. (2016)

	Designation from Study	Cl- (g m^{-2})	Cl- (mg m^{-2})	Days	$\text{mg Cl}^{-} \text{d}^{-1} \text{m}^{-2}$
<i>J. torreyi</i>	JT-2	111.30	111300.00	126	883.33
<i>T. latifolia</i>	TL-3	94.80	94800.00	126	752.38

Consideration of Parametric Equation Limitations

This final chloride uptake equation in the far right column of Table 10 is ready for use, but this rate is dependent on specific conditions as stated in the study. Specifically, these limitations and conditions are the time of year (late spring 15 May is the beginning of the experiment) and the number of harvests with each scenario. For the scenario JT-2, the number of harvests were two during this 18-week experimental study. For TL-3, the number of harvests were three times over the period of the study. Finally, standard error was reported for the scenarios uptake rates and therefore should be reflected in our calculations. These conditions and limitations are important to note, as they may have implications for their use in the database. For instance, the time of year chosen is the peak growing period for most plants and the parametric Cl^{-} uptake equation could be affected by year-round operation instead of just during the summer. Similarly, the number of harvests could affect the amount of labor required to maintain

this specific chloride uptake with these plants. Finally, the error associated with the measurements could have implications for the sizing of the constructed wetland to make certain a specific Cl^- uptake is achieved in an engineering application. CHAPTER 6 of this dissertation provides further explanation of this application.

The adoption of the process presented above in Figure 16 towards the discovery of new biological, technological, and hybrid material and energy recovery strategies facilitated in the population of the database presented in the following section of this study. As one may suspect, this process is time intensive and requires considerable effort to produce just one of these “decomposers”. However, it is the hope of the author that this database will serve as an ever-expanding list of potential resource stream reclamation solutions through the use of technological, biological, and hybrid “decomposers”.

4.4 Results and Discussion: A Database of Engineered Systems That Mimic Nature’s Decomposer Functional Role

Through the literature review approach outlined above, a dataset of 68 energy or material recycling strategies were compiled and presented in in APPENDIX B. Full Database of Biological Technological and Hybrid Solutions, to include 52 biological, 9 technological, and 7 hybrid waste stream interventions. While these systems represent a small fraction of the possibilities to increase cycling in the built environment, the characterization and classification framework presented above proposes a modular platform for expansion for use by subject matter experts and the design community. Each of these solutions incorporate key components found in the decomposer functional role from natural ecosystems such as breaking down complex matter/energy into fundamental

components and making this matter/energy available again for use in the system or elsewhere.

A snapshot of this database is shown below in Table 11 and Table 12. The full database can be found in APPENDIX B. Full Database of Biological Technological and Hybrid Solutions. Table 11 below shows a snapshot of the structural connections included in the database that includes possible waste stream matches and potential methods of recovery. Table 12 below expands on the structural connections to include the parametric equations needed to estimate flow values of these biological, technological, or hybrid “decomposers”. Table 11 and Table 12 are combined in the APPENDIX B. Full Database of Biological Technological and Hybrid Solutions, but are separated in this chapter to facilitate easy viewing.

Table 11. Snapshot of Structural Connections Database that Includes Biological, Technological, and Hybrid Solutions to Waste Streams.

Waste Stream	Waste Category	From Class	To Class	Waste Number	Individual Waste	Treatment Method	Method of Recovery
Air Pollutants	Chemical	C,D,F,G,I,J,K,N,O,R	B,C,D,F,I,J,K,L,M,N,O,R	1	NO2	Ecological	Green Roof
				2	Ozone (O3)	Ecological	Green Roof
Fly Ash	Ash	C,I,R	A,B,E,K,M,R,S	3	Lignite Coal Fly Ash	Technological	Zeolite Transformation Under Atmospheric Conditions
Food Waste	Organic	A,F,K,N,R,S	A,C,F,I,K,M,R,S	4	Cheese Whey	Ecological	Fermentation Using Microbial Strain (Recombinant E. coli)
				5	Molasses	Ecological	Fermentation Using Microbial Strains (Mixed mesophilic cultures)
				6	Wheat Starch	Ecological	Fermentation Using Microbial Strains (Mixed mesophilic cultures)
				7	Peanut Shell	Technological	Pyrolysis
				8	Digestate	Technological	Pyrolysis
				9	Hazelnut Shell	Ecological	Bioconversion via SHF with <i>Saccharomyces cerevisiae</i>
				10	Kitchen Waste	Hybrid	Codigestion

Table 12. Snapshot Flow Connections Database that Includes Biological, Technological, and Hybrid Solutions to Waste Streams

Waste Number	Method of Recovery	Treatment Rate	Rate Units	Fate	Limitations	Requires Further Post-Processing (Refinement)	Source
1	Green Roof	1.03	$\text{g m}^{-2} \text{ yr}^{-1}$	Deposition onto plants	112 \$ m ⁻² cost average for extensive install, but highly variable	FALSE	(Manso, Teotónio, Silva, & Cruz, 2021)
2	Green Roof	1.96	$\text{g m}^{-2} \text{ yr}^{-1}$	Deposition onto plants	112 \$ m ⁻² cost average for extensive install, but highly variable	FALSE	(Manso et al., 2021)
3	Zeolite Transformation Under Atmospheric Conditions	0.5	$\text{g g}^{-1} \text{ yr}^{-1}$	Zeolite Na-X (useful for soil/groundwater remediation of heavy metals such as Cd through adsorption)	Needs alkaline activator sodium hydroxide at rate of 1.5 mol/L NaOH	FALSE	(Zgureva, Boycheva, Behunová, & Václavíková, 2020)
4	Fermentation Using Microbial Strain (Recombinant E. coli)	0.33	$\text{g L}^{-1} \text{ h}^{-1}$	PHA - Bioplastic (biomedical, agricultural and industrial applications)	Needs Batch Bioreactor Infrastructure	FALSE	(Pais et al., 2014)
5	Fermentation Using Microbial Strains (Mixed mesophilic cultures)	4.8	$\text{L L}^{-1} \text{ d}^{-1}$	Hydrogen Gas		FALSE	(Ren et al., 2007)
6	Fermentation Using Microbial Strains (Mixed mesophilic cultures)	3	$\text{L L}^{-1} \text{ d}^{-1}$	Hydrogen Gas		FALSE	(Hussy, Hawkes, Dinsdale, & Hawkes, 2003)
7	Pyrolysis	.3-.43	$\text{g g}^{-1} \text{ hr}^{-1}$	Biochar	Horizontal tube furnace 300-950 deg C	FALSE	(Elkhalifa, Al-Ansari, Mackey, & McKay, 2019)
8	Pyrolysis	.35-.6	$\text{g g}^{-1} \text{ hr}^{-1}$	Biochar	Fixed bed horizontal tube 300-700 deg C	FALSE	(Elkhalifa et al., 2019)
9	Bioconversion via SHF with <i>Saccharomyces cerevisiae</i>	0.0057	$\text{mg ml}^{-1} \text{ hr}^{-1}$	Bioethanol (44.89% maximal ethanol yield)	Requires LHW near critical water pretreatment before bioconversion; max ethanol production is 200C, 2 ml min ⁻¹ flow, and 200 bar; Max ethanol productivity at 0.5g solid loading	FALSE	(Uyan, Alptekin, Cebi, & Celiktas, 2020)
10	Codigestion	582.53	$\text{kg kg}^{-1} \text{ d}^{-1}$	Methane Gas	Produces (6.93 t biogas d ⁻¹) , (10.3 t digested sludge DM d ⁻¹), and (2.19 t methane d ⁻¹) from inputs of 7.15 t Sewage Sludge DM d ⁻¹ , 4.68 t Municipal Biowaste DM d ⁻¹ , 1.28 t Kitchen Waste DM d ⁻¹ inputs. Assumes densities of 1.2 kg m ⁻³ for biogas and .669 kg m ⁻³ for methane	FALSE	(Blank & Hoffmann, 2011)

Table 11 shows a snapshot of ten of these “decomposers” potential structural connections to individual waste streams in the first column. The second and third columns present the same categories and potential industries that could receive the waste streams as shown in by Raleigh et al. (1995). The next column is an individual waste number that allows for easy connection between Table 11 and Table 12. In the next three columns are the individual waste that is often further refined from that shown in by Raleigh et al. (1995) followed by the treatment method category and the “decomposing” method of recovery.

Table 12 is an extension of Table 11 that includes the waste number that corresponds to Table 11 in the first column. The second column is the repeated method of recovery, followed by the treatment or transformation rate and the units associated with that rate. In the fifth column is the fate of the waste stream after recovery followed by the limitations to the treatment and transformation rate. The final two columns represent the Boolean value requiring further post-processing and the academic source.

4.4.1 *Feasibility Considerations*

Assessment of the overall feasibility of each of the technological, biological, and hybrid solutions presented in this dataset will be an essential step in its future application. Studies suggest that feasibility assessment of sustainability interventions should account for costs, sustainability performance, and stakeholder considerations (Shen, Tam, Tam, & Ji, 2010). Given that the application of each of the solutions requires a myriad of additional design considerations, an example is provided below for the application of sewer thermal heat recovery in the built environment.

Sewer Thermal Heat Recovery Design Considerations Example

In order to begin evaluating a given intervention from the database for its applicability, there are three general steps that designers, practitioners, and government officials must consider. These general steps include: 1) evaluation of the waste material or energy that could be captured or recycled via a given intervention; 2) a thorough cost-benefit analysis and 3) a stakeholder assessment. We describe some of these in greater depth for the application of sewer thermal heat recovery to provide an example below in Figure 17.




Feasibility Category	Specific Steps	Sewer Heat Exchange Examples
 Material or Energy Recovery Potential	Demand	<ul style="list-style-type: none"> o Calculated through energy and mass balances o Refer to Department of Energy statistics on energy usage by home and region
	Potential Supply	<ul style="list-style-type: none"> o Estimating sewer's capacity to act as a source/sink o Estimate energy potential from up/downstream flows of existing/future infrastructure <ul style="list-style-type: none"> o Alternative: Sewer Diameter, Depth, and Slope o Alternative: Indoor Potable Water Usage
	Sizing & Placement	<ul style="list-style-type: none"> o Consideration of line losses (e.g. pressure, energy, etc.) o Consideration of building phases and timeline to integrate
 Cost/Benefit Analysis	Cost Potential & Baseline Estimate	<ul style="list-style-type: none"> o Utility rates and existing/proposed sewer infrastructure <ul style="list-style-type: none"> o Local electricity costs o Local gas costs o Local water utility costs o Infrastructure costs (from potential tap location, distance, and routing)
	Benefits Analysis	<ul style="list-style-type: none"> o Return on investment o Building footprint impacts o Noise and air pollution reduction o Water conservation
 Stakeholder Assessment	Governance	<ul style="list-style-type: none"> o Governmental & municipality engagement o Regulatory landscape and fee structure
	Population	<ul style="list-style-type: none"> o Surveys, feedback, engagement
	Environment	<ul style="list-style-type: none"> o Impact to current wastewater temperature (positive & negative)

Figure 17. General Feasibility Considerations with Example

To assess the potential material or energy recovery potential of the sewer thermal system, we propose one begin by conducting a mass and energy balance of the proposed engineered system. This will involve determination of both the thermal energy demand of the proposed project building site, either for hot water production, environmental heating

and cooling, or others. The energy and mass balances in addition to the Department of Energy statistics on energy usage by building, home, and region can facilitate calculations. Next, one should determine the potential energy supply by estimating the sewer's capacity to act as a heat source and/or sink. This will likely involve the estimation of upstream and downstream sewer flows with and without existing sewer infrastructure, accounting for future developments. Finally, designers can determine optimized placement and sizing from overlaying demands with site plan with attention to line losses and building phases and timelines.

Following the energy potential evaluations, one should determine the potential cost and baseline cost estimates for the implementation of sewer heat exchangers. Studies indicate that economic considerations are the most important determining factor for decision making in urban redevelopment schemes (Hunt & Rogers, 2005). Such considerations will require accounting for both utility rates and existing/proposed sewer infrastructure. A thorough cost analysis will also take into account the local electricity, gas, and water utility costs given the size of the potential project. Infrastructure costs, determined from potential tap locations, distance, and routing, should also be included in cost models. Costs will then need to be reconciled given the potential benefit of such interventions, which can be captured by a benefits analysis. Such analysis will account for returns on investment (ROI), sewer fees for tapping infrastructure, potential environmental footprint improvements, including water use and energy returns, as well as additional footprint considerations, and potential effects such infrastructure will have on current wastewater temperature and additional downstream impacts.

In addition to cost and energy accounting described above, stakeholder assessment is another critical layer of the feasibility assessment process. Stakeholder assessments will capture local hurdles and champions, which can make or break the ultimate infrastructure project viability (Shen et al., 2010). Additionally, stakeholder assessments must consider the will of local water authorities, including the potential for revenue generation and incentives, which can reinforce public acceptance or municipal buy-in.

This provides some examples of specific considerations that will likely be required in order to evaluate the feasibility of a given intervention. However, these considerations in this feasibility analysis is by no means exhaustive. Additional considerations are likely, and must be decided upon by local governing authorities, designers, and engineers prior to adoption of any material or energy recovery strategy from the database presented in this study.

4.4.2 Broader Discussion of Results Using Waste Stream Matching to the Fields of Industrial Ecology and Circular Economy

Waste management in industry is one of the principal environmental problems in both developed countries and growing in emerging economies (Agamuthu, 2008). Prior work has shown it is essential to introduce new control measures where these wastes are generated for maximum sustainability benefit (Kourmpanis et al., 2008; Villoria Sáez, Del Río Merino, & Porras-Amores, 2012). In addition, the identification of inputs and outputs at the company level is also essential to finding new opportunities for collaboration among industries (B. Song, Yeo, Kohls, & Herrmann, 2017). However, identifying these inputs/outputs is often expensive and time consuming (Hein, Jankovic, Farel, & Yannou,

2016), and control measures vary greatly from country to country. In addition, some companies are less willing to share their waste-related information and instead prefer confidentiality (Bacudio et al., 2016).

To address some of these problems, researchers have attempted to classify and quantify industry wastes from a top-down approach in order to facilitate a transition to more circular approaches to waste management strategies (Barnard & Olivetti, 1990; Grant, Seager, Massard, & Nies, 2010; B. Song et al., 2017). For instance, in Europe industrial wastes are classified according to the European Waste Classification for Statistics, which has enabled researchers to develop a standardized approach to explore potential industrial symbioses (Patricio et al., 2020). While this has enabled the development of a method and two databases that support implementation of circular economic principles, prior work is largely limited in their focus on waste streams produced by bio-based industries and their application for use as inputs for biogas production.

Alternatively, this study has demonstrated a modified top-down approach to waste-stream matching in industry that also translates the usual (and broadly) classified waste streams to a more refined state. This refinement adds to the potential of this databases use across the industrial landscape in CE, because it not only identifies industries that can share wastes, but also decomposers that may address unmatched wastes. This also empowers companies in industry by providing several possibilities to handle waste streams; some of which may be more profitable routes by utilizing these “decomposers” in the database over waste stream matching with other industries. It is suggested that future work look to expand this database to its fullest extent to not only connect industry waste streams with other industries, but also address fundamentally these waste streams at their source.

4.5 Summary and Conclusions

In the previous chapter, we found that Finn Cycling Index (FCI) and Linkage Density (LD) were the two ecological metrics from Ecological Network Analysis that most succinctly explained the greatest degrees of variance amongst an analysis of 100 ecosystems. In order to translate these learnings to engineered systems design, this chapter provided a means to generate a database of biological, technological, or hybrid systems that, if introduced into engineered systems, could directly increase the ecological metrics LD and FCI by mimicking the decomposer functional role in ecosystems.

These systems were classified and characterized based on individual waste categories using the NAICS standard. This classification and characterized scheme will allow for easy searchability through waste matching for designers. The biological, technological, or hybrid interventions also included parametric equations that approximate treatment capacity that describe the performance, sizing, and limitations of the solution when applied and is backed by academic literature.

The academic sources that accompany the databases' biological, technological, or hybrid interventions establish their functional parameters, limitations, and initial feasibility when applying these interventions in an engineered system. This chapter also provides a breakdown of design considerations to establish a more in-depth feasibility considerations one might encounter when using this database. This is provided through an example in the application of Sewer Thermal Heat Exchangers in an engineered system and highlights the recommended depth that designers or academics should explore when using this database.

Future work should focus on expanding the database using the methodology provided. As stated in this chapter, determining these biological, technological, or hybrid solutions requires considerable effort and the current level of coverage for waste streams is in its infancy. Therefore, we also suggest future work should examine the possibility of incorporating solutions such as machine learning to overcome or automate the work required for populating this database further. The ensuing chapter will now shift focus in this dissertation to applying these biological, technological, or hybrid solutions in engineered systems with a generalized ENA mathematical modeling framework.

CHAPTER 5. A GENERALIZED ENA MODELING METHODOLOGY AND ITS APPLICATION TO ENGINEERED SYSTEMS

In CHAPTER 3, it was determined that Linkage Density (LD) and Finn Cycling Index (FCI) were fundamental structural and flow-based ecological metrics that explain the majority of the data variance when examining over 100 natural ecosystems. In CHAPTER 4, we presented a dataset of biological, technological, and hybrid interventions that best mimic the decomposer functional role in ecosystems, nature's core recycling component. We know from the formulation of FCI and LD presented in CHAPTER 2 that the incorporation of these interventions would lead to increased LD and FCI when applied to engineered systems and they provide a means of breaking down dissipated (lost to the environment) material or energy and upcycle it back into the system for use or export. However, the exact approach to applying these interventions for a systems-level sustainable improvement of engineered systems in a general manner is not well established. Current techniques of applying ENA rely on experts with a knowledge of both engineered systems and the foundations of ecosystems ecology along with the inherent assumptions and intricacies of modeling one in terms of the other. (Astrid Layton et al., 2016a; Stephen M. Malone, 2017; S. M. Malone et al., 2018; Stephen M. Malone et al., 2018). Clear definitions and an outlined approach for successful implementation are needed to overcome the steep learning curve of applying these techniques for modeling and improvement of an engineered system using ENA.

Therefore, the objective of this chapter and fundamental contribution is to develop both a generalized model to describe engineered systems components and a quantitative

ENA modeling methodology (ENAMM) to analyze a system of these engineered components from an ecological perspective. We then provide examples of ENAMM's implementation by investigating two case studies from automobile manufacturing and carpet manufacturing that emphasize what may be achieved by structural changes (e.g. changes to LD) versus changes to flows through established components.

In the first case study of an automobile manufacturing facility, the analysis considers simple structural modifications to improve its ecological metric values for the facilities energy, material, and water systems. This case study stops short of exploring the distribution of flows in the network, or the associated costs with implementation of the suggested modifications. However, it provides an in-depth analysis of the initial stages of the ENAMM– the underlying assumptions one might propose, the identification and establishment of system boundaries, and the identification of the correct level of coarseness when breaking the high-level systems down to the components inside system boundaries.

In the latter case study of a carpet manufacturing recycling model, we show a flow-based analysis using ENAMM. This case study highlights the later stages of the modeling approach that the automotive case study did not explore – the improvement of ecological metrics for these systems, the consideration of economic potential brought about by this approach, and one method for incorporating multi-objective optimization into the modeling process to balance cost and ecological metric improvements.

5.1 Research Tasks and Goals to be Addressed

This chapter contributes to the completion of Research Tasks 4, 6, and 7. These tasks contribute to the research goals Research Goals 1.5.1 and 1.5.3.

5.2 Background

In this age of increased connectivity, the buying power of the increasing number of environmentally conscientious consumers has encouraged leading industries to embrace sustainable design. Consequently, designers and decision-makers have come to recognize the economic incentives provided by improvements to the environmental and social components of their value chains. In an effort to aid designers, multiple planning and building strategies have been established to minimize the environmental burdens wrought by large projects. Well known Green Building Rating Systems (GBRS) include the Leadership in Energy and Environmental Design (LEED) rating system in the United States (Bernning, 2008), German Sustainable Building Council System (DGNB) in Germany (DGNB (German Green Building Council), 2011), and Building Research Establishment Environmental Assessment Methodology (BREEAM) in the United Kingdom (BRE Global Ltd, 2014). These GBRS convey material use and selection standards, energy and water consumption policies, site selection parameters, and operation and management guidelines. Attempts at managing and unifying these guidelines have been made at regional and national levels, but most of these focus on the building scale (Collinge et al., 2015).

Discussions with partners in private industry revealed that many planners and large-scale development firms have their own internal documentation seeking to align business objectives and industry standards with environmental policies while catering to client preferences on a case-by-case basis. Although these sustainable design methods can reduce project-specific impacts, the common frameworks are either: (1) entirely subjective in nature – requiring the designer to make decisions based on loosely-structured sustainability

objectives and often lacking a quantitative methodology – or (2) only guide decision at the unit-process level and neglect the multiple interactions and interdependencies among system components. As such, they fail to capitalize on potential systems-level performance and sustainability. Without rigorous quantitative benchmarking tools, designers are unable to model the macro-level performance during the design phase and must rely on guiding principles that may not be well understood or effective.

While efforts have been made to create a unified standard for the quantification of sustainability strategies, few are regarded with as much esteem as the Life Cycle Assessment (LCA) framework outlined by the International Organization for Standardization (ISO). LCA allows sustainability practitioners to make design and planning decisions based on systematic input-output analysis, and it enables decision-makers to evaluate the environmental impacts of products, processes, and materials from the systems level. ISO outlines four main steps of an LCA as follows (Bryden & Dhérent, 2009):

- 1) Goal and scope definition, at which point the practitioner defines objectives and process boundaries
- 2) Life Cycle Inventory (LCI), which is an input-output categorization of all resource input and emissions data
- 3) Life Cycle Impact Assessment (LCIA), at which point inventories are collated based on project objectives
- 4) Interpretation and improvement analysis

Product designers use LCA during the design phase, enabling material choices based on quantifiable impact assessments. Increasingly, architects and planners use the LCA methodology in order to quantify building and project impacts. Nevertheless, there are

often tradeoffs and discrepancies that arise when designers attempt to reconcile LCA with GBRS results (Collinge et al., 2015), suggesting that neither methodology alone is sufficient and that more work must be done to improve sustainable systems design in practice.

5.3 Generalized Model Formulation for Engineered Systems

This proposed general model formulation builds upon ENA models reviewed in literature that have been used for analysis, but not for design of engineered systems. This proposed formulation includes the definition of a system component with the addition of constraints and transformation energy requirements, costs, and distance considerations in order to achieve practical design decision-making applicability. One example of the practical considerations a designer might face when attempting to integrate system components is shown for a Sewer Thermal Heat Exchanger in Section 0. The workflow for building this general model formulation begins with the characterization of the different components and the constraints on their storage properties and throughput, input and output flows, and energy requirements for conversion of these inputs into their respective outputs.

5.3.1 Generalized System Component Model

The general system component is the backbone of the proposed systems modeling approach. The system component uses a black box approach to simplify varying scales and complexity of infrastructure or equipment to a simple input and output scheme. The level of detail or coarseness a designer should break a system of systems down to individual system components is addressed in the next section. A system component in this approach is defined by 6 types of information:

- 1) System component properties, which identifies key constraints on throughput, location, and storage
- 2) Flow into and flow out of the component
- 3) Recoverable waste not yet utilized by adjacent components
- 4) Transformation energy, required by the system component to transform inputs into outputs to adjacent components
- 5) Unrecoverable losses produced by the transformation processes

Figure 18 shows how this information is connected is shown in the simplified diagram below.

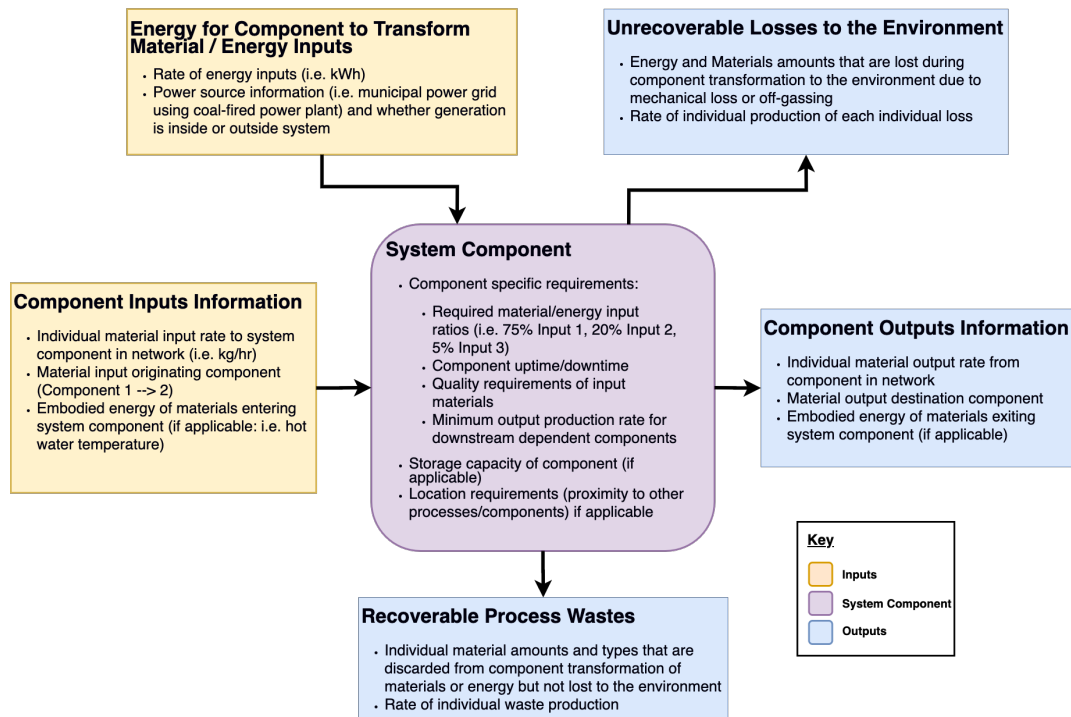


Figure 18. System Component Definition

Natural ecosystems are governed by the laws of thermodynamics. Therefore, the inputs (yellow) and outputs (blue) in the system component model should also follow the basic principles of conservation of mass and energy. Therefore, the system component should be balanced, as should the adjacent system components, to form a balanced systems model when all components of the system are defined. The diagram is simplified in that

there may be many inputs and outputs to a system component, however each system component must have the information listed to follow our proposed ENAMM to completion.

The accuracy of the assignment of values in the system component will directly impact the accuracy of the results at the end of the proposed ENAMM. Therefore, a designer should base flow approximations on well-researched assumptions and adhere to known flow values based on real-world performance when available. A sensitivity analysis can uncover the exact impact approximated flow values have on the model results.

5.3.2 Generalized ENA Modeling Methodology (ENAMM)

There currently is no established methodology for modeling engineered systems using ENA. Therefore, a main contribution we seek to develop is design guidelines, general rules, and suggested recommendations for future researchers and industry professionals wishing to model engineered systems using ENA. Our proposed modeling approach is shown below in Figure 19.

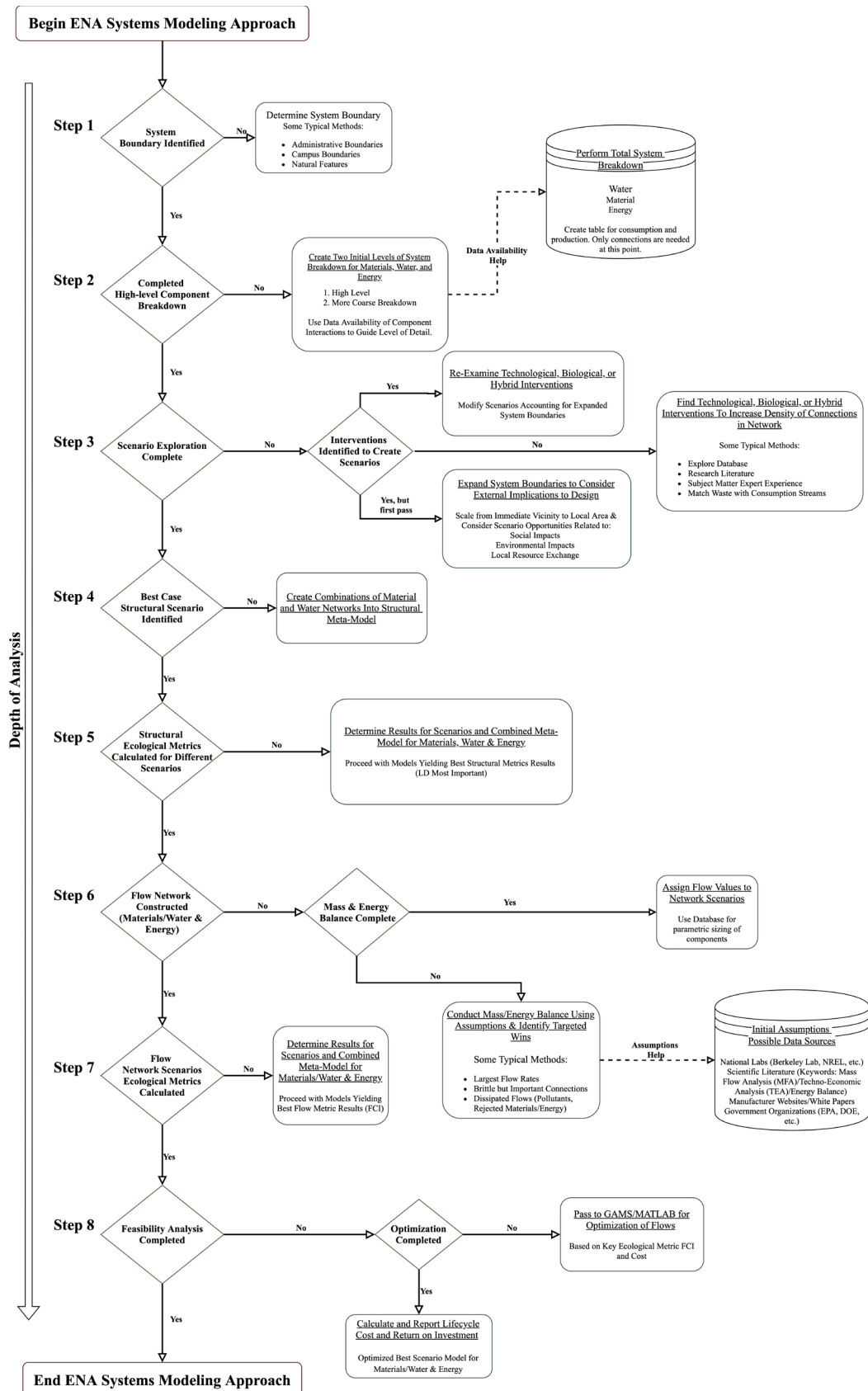


Figure 19. Generalized ENA Modeling Methodology (ENAMM) for Engineered Systems

5.3.2.1 Step 1: System Boundary Identification

When ecosystems are analyzed using ENA, they are typically limited to a specific geographic area or habitat boundaries such as a wetland, estuary, lake, or sea. These geographic boundaries are relatively easy to identify, such as the shore to a lake. However, engineered systems are not always subject to the constraints of their environments. Attempting to develop a general rule to encompass the entirety of possibilities in the engineered world is futile. Therefore, when applying ENA to the built environment in engineered systems, it is best practice to adhere to geographic limitations to include administrative boundaries, campus boundaries, or natural features. The method a designer chooses as a rule must be noted in the assumptions of the model.

When clearly delineated boundaries are not available, the designer must use best judgement. Solar energy is the biggest outside influence on natural ecosystems by providing the basis for functionality and cannot be changed for life to persist. When ecosystems are analyzed using ENA, the analysis stops short on including the sun but includes organisms that feed on it, such as phytoplankton in aquatic ecosystems or plants in terrestrial ecosystems. This is standard practice for ENA of ecosystems by ecologists and is incorporated by the standing stock of plant biomass that reflects growth over the year. The non-captured energy from the sun is not relevant and therefore this flow is not necessary to be reflected in the network. This is primarily because the input is not limiting and secondly because there is no use for the excess.

In engineered systems, there is a similar denotation of imports or exports of materials or energy to and from the system. However, this line is sometimes blurred. At a campus level hospital or university, you may have one or two central utility plants that generate power. However, grid electricity may supplement these utility plants to meet peak power demands. In this case, it would be recommended that the central utility plants for the campus to be included, while grid electricity be excluded. Further examples will be provided in the case studies and chapters to follow to provide more clarification to the establishment of system boundaries.

5.3.2.2 Step 2: High-Level Component Breakdown

One of the most challenging aspects in the initial phases of modeling engineered systems using ENA is pairing down a high-level model to appropriate levels of detail. If a model is too simple, the results will not accurately reflect system behavior. Alternatively, if a model is too complex, the lack of data availability limits the analysis. Oftentimes, the coarseness level in a model is often dictated by data availability. However, there are several other considerations when examining how ecologists simplify ecosystem models.

ENA models of natural systems often include aggregated species such as detritus feeders and decomposers into one group because they are functionally similar. The degree of this interaction can affect results in ENA models, and experts in the field suggest maintaining the same level of detail among system components (Brian D. Fath & Patten, 1999). Therefore, our ENA modeling methodology suggests the same or similar level of detail throughout the system. For example, if one system component is

a paint shop of an automobile manufacturing plant includes many subprocesses (washing, priming, painting, drying, etc.), another component should not be a singular robotic arm inside of an assembly shop that has no subprocesses.

5.3.2.3 Step 3: Scenario Exploration

Deep reflection of design decisions should occur in this step of ENAMM. At this step, a designer has now determined, at least from a high-level, the waste of the system components and the connections that form the overall modeled system (e.g. inputs and outputs). Knowing this, it is now up to the designer to investigate the technological, biological, or hybrid interventions that can address these waste streams and consider the basic implications of their inclusion. This may be accomplished by looking in the database supplied in CHAPTER 4, researching interventions from literature, or relying on subject matter expertise in energy, material recycling, or water systems. The rules of flowrates to-from these interventions will be discussed in Section 5.3.2.5.

An important part of this step in the proposed methodology is also considering potential opportunities outside the system boundary. A simple but effective solution to intervening in waste generation could be through diversion, by matching wastes with consumption streams nearby. This is a common tactic of Eco-Industrial Parks (EIPs). By expanding the system boundaries, a designer introduces the possibility of including social, environmental, or resource exchange opportunities. The first case study (automotive manufacturing) will explore this approach in more detail and the potential benefits that result.

5.3.2.4 Step 4 & 5: Best Case Structural Scenario and Calculation

In this step, the designer now has several scenarios they explored and the ability to choose one or a combination of scenarios to form a final structural model. This structural model should focus not only on addressing waste streams, but also increasing the connections inside the network itself by matching scenarios. The resulting structural meta-model should increase the key structural metric we found in CHAPTER 3, Linkage Density (LD). A suggested target value for our methodology is to achieve at least one and a half standard deviations ($1.5 \times 4.30 = 6.44$) from the mean value (9.99) for the 100 ecosystems analysis of LD in CHAPTER 3, or a LD value of at least 3.54. This target value is chosen due to the high standard deviation compared to other metrics we analyzed in CHAPTER 3. Previous work has shown that EIPs fall short of this suggested value, averaging around of 2.41 for LD (Astrid Layton, 2016), however these engineered systems were not designed from conception with ecological metrics in mind. Recent research has shown that with thoughtful redesign, these EIPs can achieve our recommended LD target value (Astrid Layton et al., 2017). To achieve this target goal in the final structural model created from this proposed approach, iterating the structural model to include combinations of scenarios is suggested to achieve a structure on par with that found in natural ecosystems.

5.3.2.5 Step 6 & 7: Flow Network Construction and Calculation

An ENA flow-based model of a natural ecosystem is a static representation of a dynamic system (Brian D. Fath & Patten, 1999). Most of these models represent the exchange of materials and energy in a certain time period, usually a year, and thus are a simplification of the total interaction amongst species. As such, this approach recommends this as well for the translation of ENA analysis to engineered systems. For

example, most photovoltaics on the market do not produce electricity at all hours of the day but do produce energy over the course of a week, month, or year. Therefore, an ENA model of an engineered system that includes photovoltaics should include the appropriate time period to reflect the system component performance. The goal of this is to not exclude those system components you wish to consider.

When ecologists use ENA to measure the performance and characteristics of ecosystems, the flows are typically measured in mass or energy over this established time period as one organism consumes another or in decomposition (Robert E. Ulanowicz, 2004). In the formulation and calculation of ENA metrics, there are no constraints on the units of choice, as long as the units themselves are consistent throughout the network. This is why we recommend as a general rule that in flow-based analysis materials and water may be combined, but the energy network should stand alone. A caveat to this rule is if those energy metrics can be converted in some way. See CHAPTER 6 where energy flows in a case study are converted to material flows by approximating them as Tons of Coal Equivalent (TCE). This is what is known as a common currency and is a distinguishing factor between structural and flow analysis in ENA.

Creating a mass and/or energy balance is required when determining the material and energy flows in an engineered system. This is often a precursor in the planning and design process, and will provide the majority of the required information to complete a flow-based ENA model of an engineered system (Foran, 2019). However, there will be times when flows of materials and energy must be approximated. For these times, there are many tools and performance data from sources such as scientific literature

(using keywords such as Mass Flow Analysis (MFA), Techno-Economic Analysis (TEA), Life Cycle Analysis (LCA), and energy balance), manufacturer websites for engineered system performance data (Coefficient of Performance (COP), efficiency, energy consumption, flow rates, conversion rates), and government organizations (national labs [NREL, Berkeley Lab, ORNL, etc.], EPA, DOE, NASA, NOAA). These sources can help guide assumptions in assigning data flows and provide rigor to the ENA model. However, this process is time and calculation intensive for the designer. Therefore, the creation of a predefined database of classified waste streams and characterized parametric equations greatly assists in estimating component size, flowrates, and potential costs.

5.3.2.6 Step 8: Feasibility Analysis

In the final stage of ENAMM, the user is to determine the feasibility of the suggested design. Costs of the individual components should be based on anticipated sizing, but often more in-depth holistic considerations are needed to determine the components influence of total system cost to include both capital and operational costs. An example of this is presented in CHAPTER 4 section 4.4.1 for sewer thermal heat exchangers.

The ability to reuse or offset treatment or disposal costs of waste streams leads to decreased overall system operation cost. If this cost can offset the initial capital costs in a reasonable period, then this is a win-win scenario for both the environment and the client of the designer. It is incumbent upon the designer to explain in detail the

importance of total cost of ownership and drive economic discussions away from capital costs alone.

Mathematical modeling and optimization is a tool that can aid in balancing the overall system flowrates to both minimize costs and meet critical demands. We recommend in this step that it can also be used to balance cost reduction while achieving target ENA goals. This is similar to the recommendations in Step 4 of this methodology with the structural metric LD. The optimization should focus on the flow-based metric FCI, as in this step, the system structure is established. In CHAPTER 3, we determined the average value for FCI was 0.09 with a low standard deviation of 0.08. Therefore, we suggest meeting or exceeding this value to offset the capital costs of the initial investment into biological, technological, or hybrid interventions through reduced operational expenses.

The following sections will explore in detail the application of this eight step ENAMM in two case studies.

5.4 Case Study 1 – Automobile Manufacturing

Step 1 of General ENA Modeling Methodology (ENAMM) from Figure 19 – Identify System Boundaries

This case study is of an automotive plant in the southeast United States of which an aerial view is given in Figure 20. This plant formed the basis for the system boundary in this study. However, the modeling was not restricted to the current facility boundaries but also examined the possibility of integration with the surrounding communities.

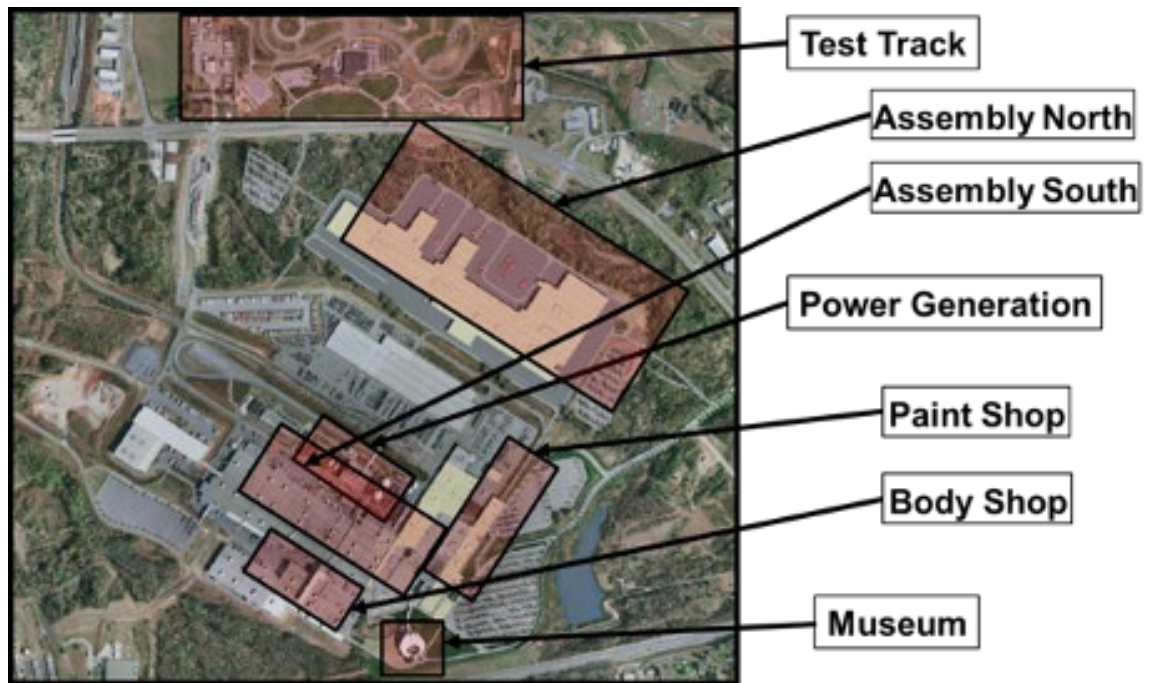


Figure 20. Automobile Manufacturing Plant

A model representing the system in terms of production and consumption must be created to accurately assess the automotive production process. The model is based on the interactions of an automotive assembly plant including the material, water, and energy flows to and from the plant. The model represents the automotive “ecosystem” that can be directly compared to natural ecosystems through the use of ENA. The automotive “ecosystem” described here is one that consists of the overall broad components that are present in the majority of automotive manufacturing facilities. This proposed automotive ecosystem consists of system components that consume and produce energy, water, and materials that are co-located as this best resembles a real ecosystem. The initial high-level network representation of energy and material flows is shown below.

Step 2 of General ENA Modeling Methodology (ENAMM) from Figure 19 – High Level Component Breakdown

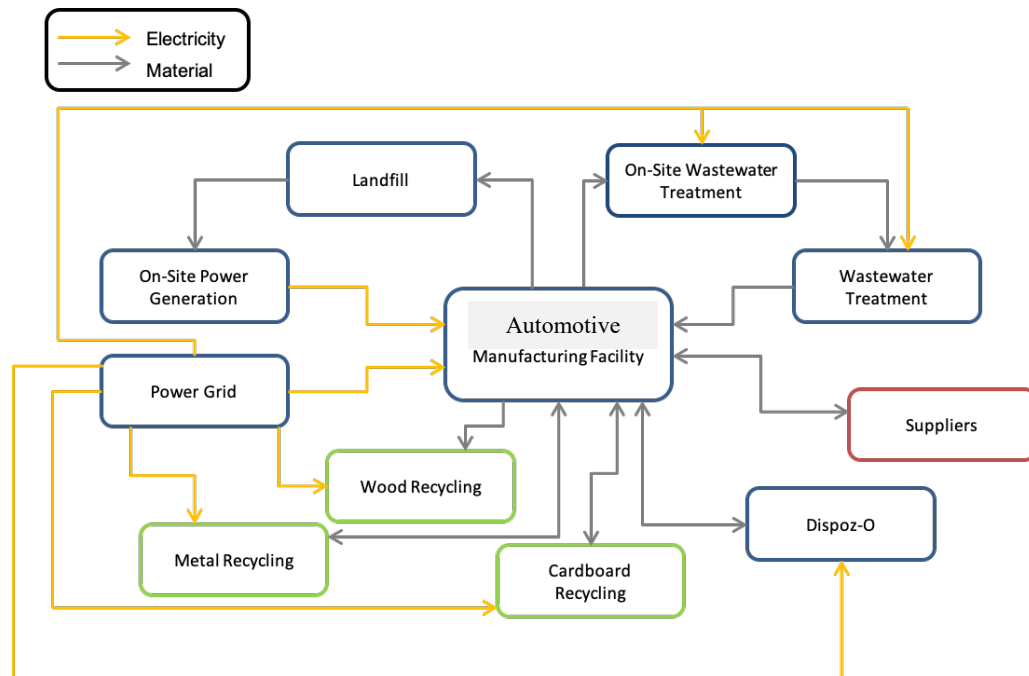


Figure 21. High-level Energy and Material Systems Model

In Table 13 below, the broad categories of system components present within the automotive ecosystem are shown and how they interact with the other components are presented. Some of the system components in Table 13 (such as agriculture) may not be explicitly or strongly integrated in the current automotive facility, but they are present in the surrounding community of many automotive facilities and thus could be easily be connected into the automotive production ecosystem.

Table 13. Component Breakdown of Consumption and Production

System Component	Consumes	Produces
Assembly Plant	Raw material Automobile components Energy Water Food Ancillary products	Vehicle Waste (Cardboard, filthy water, food, plastics, etc.)
Local Suppliers/Industry	Raw material Energy Water Food Ancillary products	Automobile components Waste (Cardboard, food, plastics, etc.)
Non-Local Suppliers	Raw material	Automobile components
Residential, Workers, Consumers	Vehicle Energy Water Food	Waste (Emissions, wastewater, food, plastics, etc.)
Agriculture	Energy Water	Food Waste (Fertilizer runoff, undesirable foods, emissions)
Landfill	Waste	
Recyclers	Waste	Raw material Ancillary products Waste (Plastics, soiled recyclables, emissions)
Energy Supplier	Raw material	Energy Waste (emissions, wastewater)
Water Supplier/Treatment	Waste Water Energy	Water (emissions, nitrogen, sludge)

5.4.1 Assumptions in the Automotive “Ecosystem”

To facilitate the modeling, the following assumptions were made with respect to a potential automotive ecosystem around a facility:

- Agriculture represents a broad range of things that are produced locally. This could include any of the following: food from home gardens that people bring into work, food from a community garden onsite at this automotive facility or another local company, local crops, tree farms, food from a farmer’s market. It is assumed that these

products are consumed locally in some capacity and therefore stay under the umbrella of the automotive ecosystem.

- All recyclers are assumed to be local and are therefore consuming local resources. These recyclers may in actuality be onsite at this manufacturing facility or a local supplier, but they are treated as a separate component. In the closed loop recycling system, it is assumed that the products created by these recyclers are consumed directly by the system components that are supplying the initial waste to be recycled.
- Wherever there is a component that does not interact with the system it is assumed that this is something that currently exists but is not being utilized. In reality, the addition of infrastructure would likely be necessary to actually utilize this (i.e. the water from an onsite pond could be used in the plant, but this would require additional piping and water treatment).
- The residential component represents the people that live in the ecosystem which includes the workers at this automotive manufacturing facility and the other local suppliers as well as the consumers that are purchasing vehicles. Obviously, the majority of vehicles are not sold locally, but it is assumed at least some will. Therefore, this component is the consumer of product produced by the assembly plant. This component also represents the interactions these people have while outside of work, i.e. at home, eating out, shopping, etc.
- Local is loosely defined for this system. There is no quantitative measure for it. It is assumed that anything that is local is drawing from the same resource pool. These resources include food, water, and energy. It is assumed these system components are

connected through some form of infrastructure and could easily exchange flows in a certain local administrative boundary.

- Suppliers are grouped into two large categories of local and non-local. Considering the number of suppliers for these vehicles, the suppliers would dominate the food web in terms of number of components (~100). Therefore, it is assumed the suppliers can be grouped together. This means that the connection between suppliers and the assembly plant represents a wide range of materials, products, shipping methods, etc. Grouping is valid in food webs when entities act the same functionally. In this context, all of the suppliers are acting the same in that they are taking in some external materials and supplying the assembly plant with an automotive component. This aggregation is justified unless there is some special waste stream or interaction with suppliers that supply a particular linkage. In our case, the internal transformations and waste streams are important so the equivalent “functionality” from ENA of ecosystems is justified.

Given these assumptions and initial description of the automotive manufacturing case study, we proceed with an ecological analysis for this automotive ecosystem.

5.4.2 Initial Structural Development

Step 3 of General ENA Modeling Methodology (ENAMM) from Figure 19 – Scenario Exploration

The initial high-level representation of the material and energy flows in the automobile manufacturing facility must be refined further to better represent the intricacies that exist but not yet represented in Figure 21. The automotive ecosystem has been broken

into three main networks that have distinct flows and characteristics. These three networks are water, material, and energy. Various improvement scenarios will be explored around these networks. These networks are all connected to one another but will be initially analyzed separately to determine the impact of a number of individual selected interventions to the waste streams in the network. The final analysis will combine these networks together to create a “best-case” structural meta-model of the overall automotive ecosystem.

This ideal automotive ecosystem considers all suggested improvements to the individual networks. The model used here is based on an automotive manufacturing plant, but many of the technological, biological, or hybrid interventions for greater sustainability are applicable in all manufacturing facilities. Certain interventions may have greater possibility of implementation or impact at other manufacturing locations. Their feasibility depends on factors such as the availability of local industries, land use patterns, or will of the local government. These other locations are not analyzed directly, but the impact of the interventions in this study may also be hypothesized for plants in different parts of the world. Each scenario for improving the networks is discussed first in the following sections, prior to performing the ecological analyses of these improvements on the network performance.

5.4.3 Water Network

Automotive production is a water intensive process. As such, the water network is a crucial component of the automotive ecosystem. The water network in this automotive ecosystem is simplified to include the main components in immediate area near the

assembly plant. The current water network structure, as shown in Figure 22, water flows from the municipal reservoir and is distributed from there.

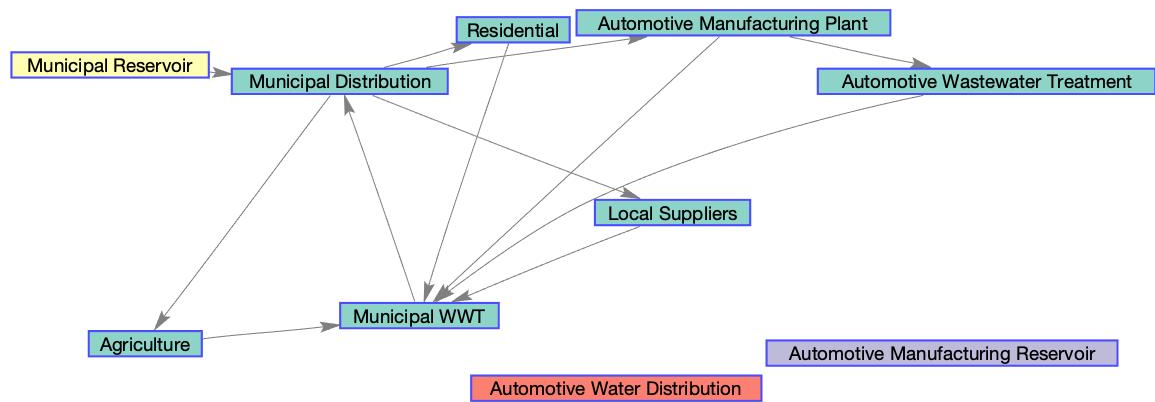


Figure 22. Original Water Network Structure. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina, Bodini, Bondavalli, & Lundbers, 2005).

The automotive plant's wastewater treatment filters out the contaminants more specific to the automotive industry, but this water is still sent to the municipal wastewater treatment facility for full treatment. In addition, all other water generated from the local components in the automotive ecosystem is sent to the municipal wastewater treatment facility and redistributed through the municipal system.

The first scenario explored in this analysis seeks to take advantage of rain capture at the automotive assembly plant and the structural changes are shown below in Figure 23.

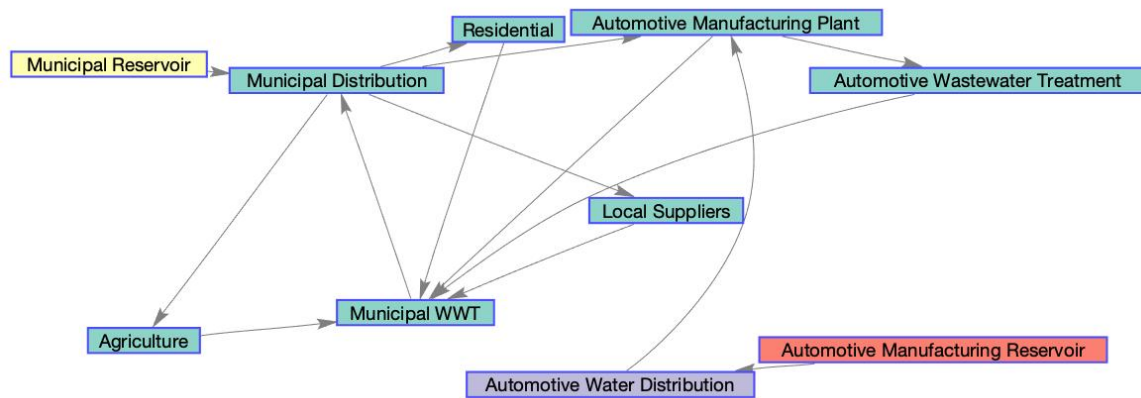


Figure 23. Rainwater Capture Water Network Scenario Exploration of the Automotive Manufacturing Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).

The automotive ecosystem in this structural configuration would capture precipitation and store the water for onsite distribution and use. This reservoir could materialize as a large retention pond located onsite or as water storage cisterns. This captured water could be used directly in certain parts of the plant such as the restrooms toilets without the need of any preliminary water treatment.

For system components requiring pre-treatment, the onsite wastewater treatment facility could be adapted to treat this water for use. Rain capture could be utilized at any automotive manufacturing facility, but the quality of the rainwater and potentials for reuse may vary between locations due to atmospheric pollution. Assuming the rain can be captured, treated, and used, this intervention reduces the amount of water needed from the municipality thus decreasing water consumption costs and dependency on facilities outside of the automobile manufacturer's control.

The second scenario, shown in Figure 24, treats gray water from the plant and uses it elsewhere in the plant.

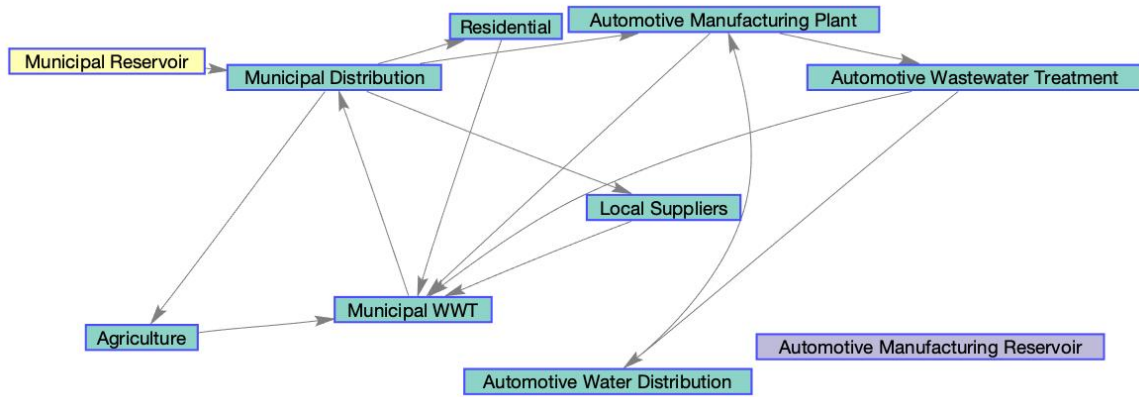


Figure 24. Graywater Systems Water Network Scenario Exploration of the Automotive Manufacturing Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).

In the second scenario, the treated gray water could be used to supply the automotive cooling towers. This assumes the onsite water treatment can be modified to treat this water properly. These cooling towers lose water due to evaporation, and need constant topping off with water from the local water supply. By reusing the water, this cuts down on water consumption and reliance from outside resources, thus reducing costs.

The final scenario for water combines the rainwater capture and gray water usage and is illustrated below in Figure 25.

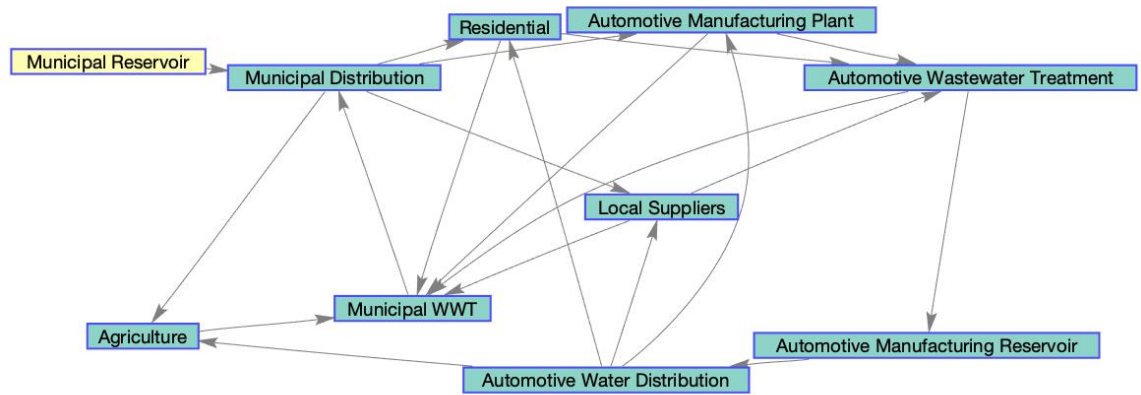


Figure 25. Combined Rainwater Capture and Graywater Utilization with Community Oriented Expansions Water Network Scenario Exploration of the Automotive Manufacturing Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).

In addition, this scenario incorporates water distribution from the assembly plant to other parts of the ecosystem, including the local community. The automotive plant would capture rainwater, be able to treat it, and send it to the surrounding area for usage. This assumes the automotive manufacturer is able to distribute to the surrounding area with agreements from the local city government. Automotive plants that are in more densely populated areas may have an easier time in implementing community water distribution. In addition, with onsite wastewater treatment, the automotive manufacturing facility may

be able to provide cleaner water than what is available from the municipality. This is more likely the case in places like India and China as opposed to the US or Europe due to local laws.

This potential expansion of the automotive manufacturer's water network complements community programs such as community-based urban agriculture, where residents and businesses integrate gardens into urban landscapes. Programs such as these provide local residents with direct access to food and other agricultural products, increasing food security and improving the local economy. The nearby cities have a number of community agricultural programs.

The different network scenarios described above were evaluated using structural ecological metrics. The resulting values for the different water networks described above are given in Table 14.

Table 14. Structural Ecological Metrics Linkage Density and Connectance for Water Network Scenario Exploration

	Community Oriented Expansions	Gray Water Treatment	RainWater Capture	Current Water Network
Linkage Density	2	1.4	1.4	1.2
Connectance	0.2	0.14	0.14	0.12

As one may observe, the rainwater capture and gray water use scenarios had similar impacts to the network structure and thus produced the same results for LD and C. However, the combined structure that includes community-oriented expansions proves to provide the best water network structure and as Figure 25 shows, nearly all of the system components are strongly connected in this scenario.

5.4.4 *Material Network*

The material network of the automotive ecosystem consists of vehicle components, packaging, office supplies, food, and all other miscellaneous materials that are used in the production of a vehicle. The main component in this ecosystem is the assembly plant alone. As such, there is not a large consumption of raw materials in the assembly of the vehicles. Instead, there is a much larger concentration of fabricated components and packaging. Depending on the exact configuration of the automotive plant being analyzed, this amount of waste varies greatly as some automotive plants consume a larger amount of raw material and thus will have more waste in those areas.

The current material network, shown in Figure 26, consists of many materials flowing to the assembly plant with little to no reuse of the material within the ecosystem. Recycling occurs, but it is assumed the majority of this material does not return to the system.

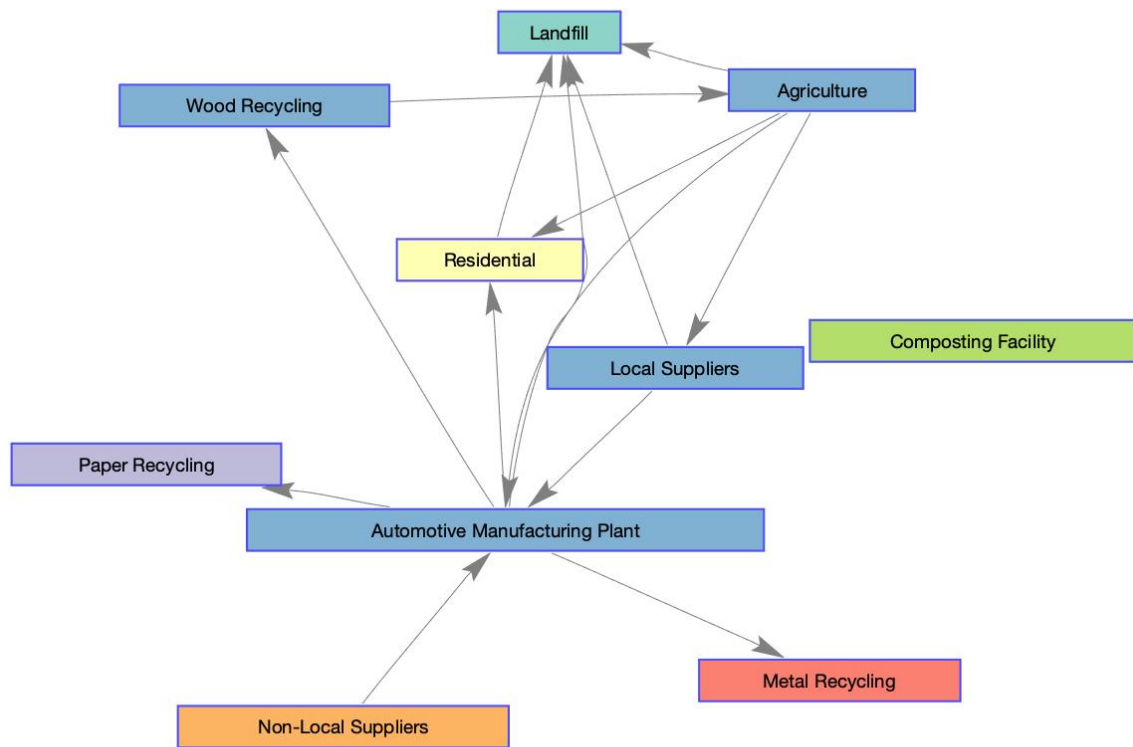


Figure 26. Original Material Network in the Automotive Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).

The first material scenario explores increased recycling, shown in Figure 27.

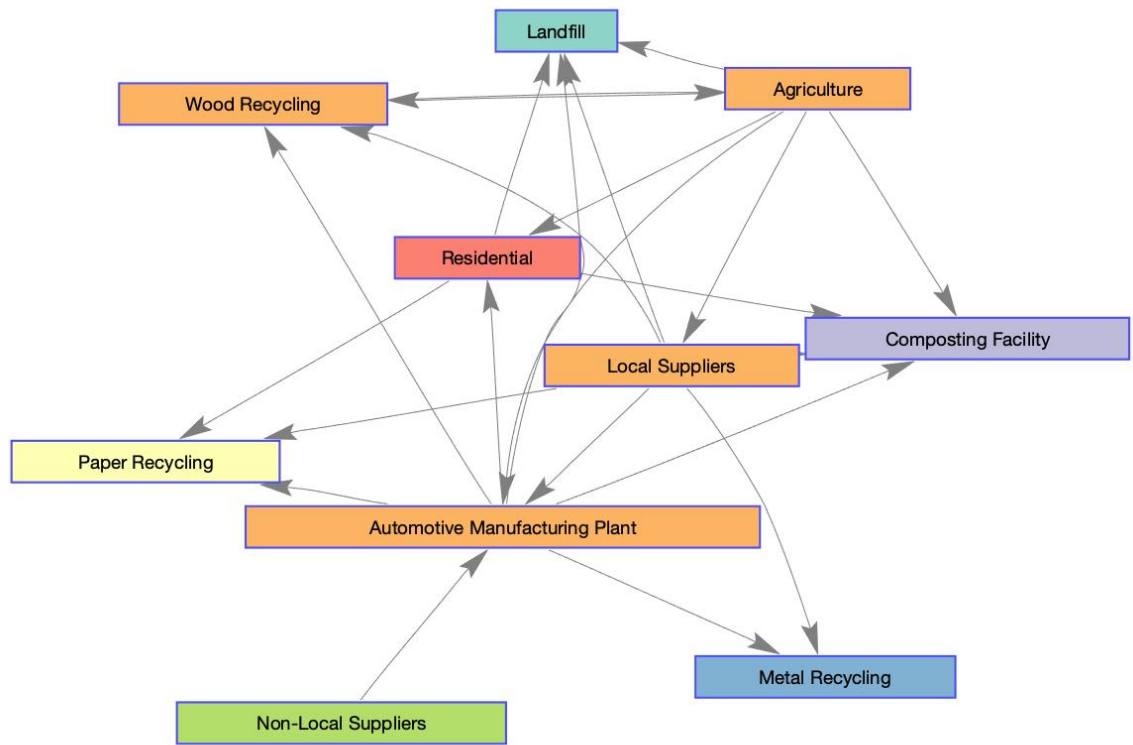


Figure 27. Increased Recycling Material Scenario Exploration within the Automotive Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).

This scenario consists of much more recycling than the current case presented in Figure 26, but still assumes that most of this recycling does not enter back into the system. The increase in the recycling is due to the addition of other system components participation. This could be implemented at all of the manufacturers automotive manufacturing locations with the main limitation being the accessibility to recyclers. If there are no recyclers, there

would be the potential for the manufacturing plant itself to create their own recycling system.

This scenario for closed-loop recycling, shown in , introduces closed loop recycling where the recycled material is utilized directly by the components in the system.

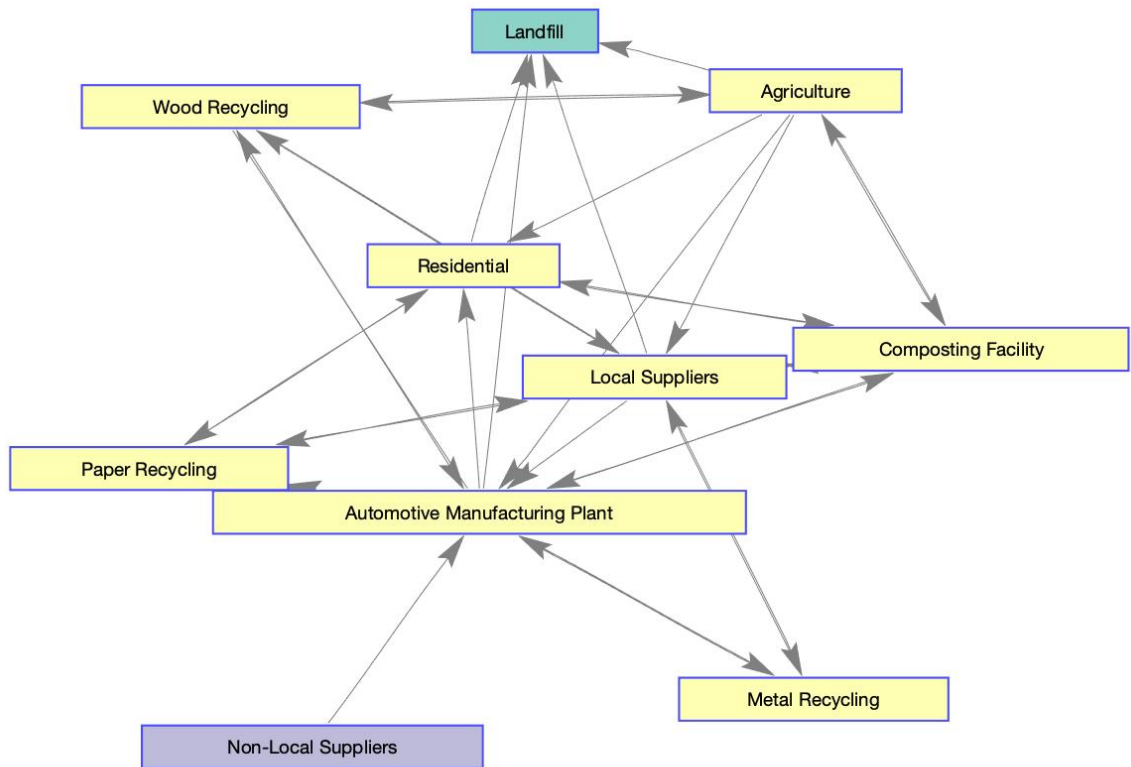


Figure 28. Closed-loop Recycling Material Scenario Exploration within the Automotive Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).

This scenario has similar limitations to the previous in that access to a recycler may be dependent on the location. In addition, this scenario will require very specific recyclers that can take the specific waste created and form a new product that can be introduced directly back into the system. Finally, this scenario may require special material selection, as some materials degrade when recycled.

The different material network scenarios described above were evaluated using structural ecological metrics. The resulting values for the different water networks described above are given in Table 15.

Table 15. Material Scenario Structural Ecological Metrics Results

	Closed Loop Recycling	Increased Recycling	Current Material Network
Linkage Density	3.40	2.30	1.40
Connectance	0.34	0.23	0.14

As with the water networks, even though the number of components remains the same in the analyzed material networks, LD is improved rather dramatically. In addition, the C in each network compared to the current material network has more than doubled. Figure 28 shows that the closed loop recycling scenarios structural configuration result in all but two of the system components strongly connected.

5.4.5 *Energy Network*

The automotive manufacturing plant currently utilizes a number of different energy sources and conversion agents, but energy is not cycled among system components. New energy is supplied primarily by grid electricity and landfill gas. Small amounts of hydrogen

gas, photovoltaic generated electricity, and energy in the form of hot and chilled water are also included. The current energy network is shown below in Figure 29.

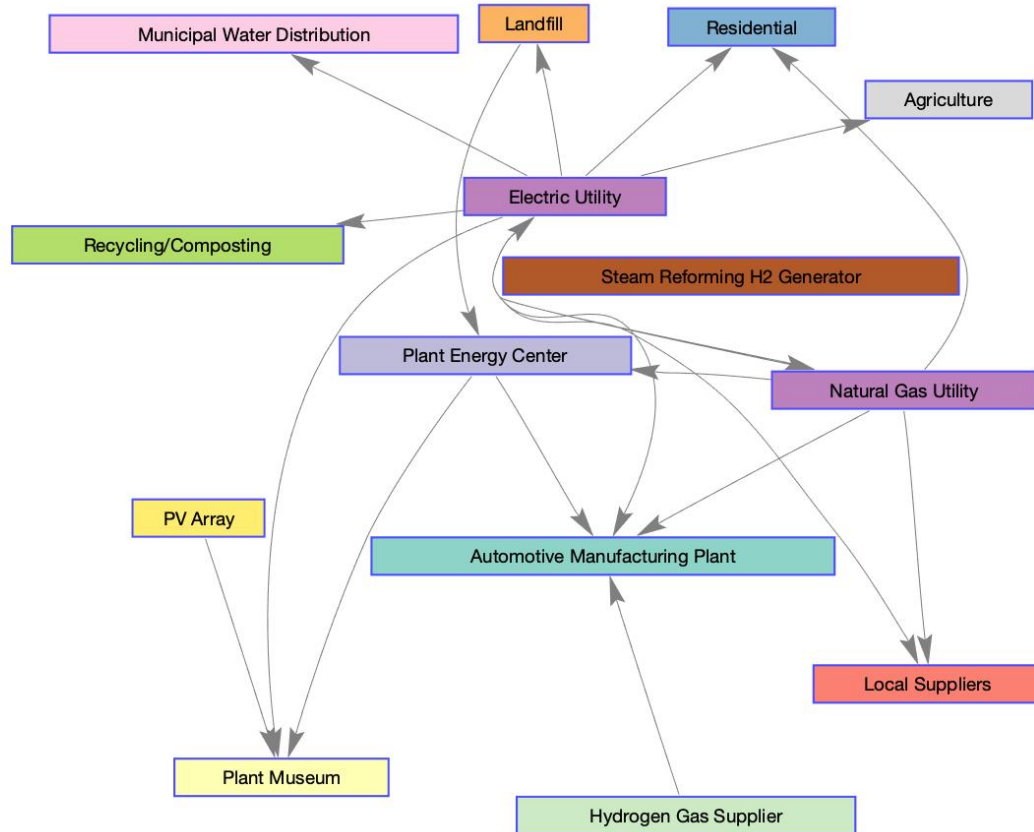


Figure 29. Original Energy Network in the Automotive Manufacturing Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).

The automotive manufacturing facility uses hydrogen to power its forklifts and part delivery carts. Allowing the automotive manufacturing plant to produce its own hydrogen would improve the functional diversity of the system and allow the plant to be organized

more like an ecosystem by allowing it to cycle energy from multiple components as shown in Figure 30 below.

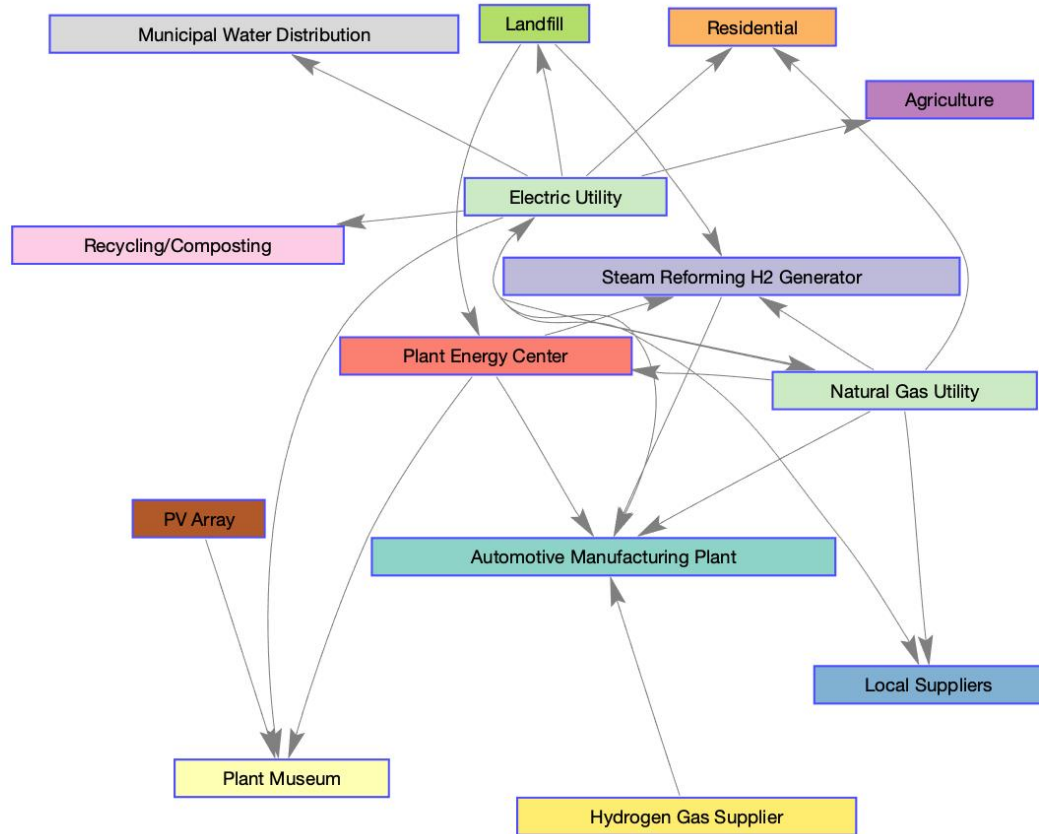


Figure 30. Hydrogen Generation Energy Scenario Exploration in the Automotive Manufacturing Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).

Instead of receiving hydrogen through an external supplier, the local communities landfill gas can be transformed to hydrogen using steam reforming of methane. Such a process is common, and the required equipment is commercially available. Assuming a steam reforming creates hydrogen with an energy conversion efficiency of 70-80%. These

hydrogen generators take in light hydrocarbons such as the landfill-supplied natural gas used in other operations around the plant.

Hydrolysis equipment also is readily available as an alternative to methane reforming. Hydrolysis is a process that uses electricity to generate hydrogen from water. Water for this process may be sourced from the plant's rainwater collection, reservoir, or treatment systems, depending on the cleanliness and salinity of the water. Hydrolysis systems operate at 70-85% efficiency from electricity. In general, hydrogen generation from steam reforming is more affordable when methane is available. However, the addition of Hydrolysis equipment would allow for a more adaptable hydrogen supply, as the plant could then generate hydrogen from either a PV array, grid electricity, or landfill gas electricity.

Another scenario this analysis explores is incorporating the automotive manufacturing plant into a microgrid with the surrounding community. A potential implementation of such a micro grid network is given in Figure 31.

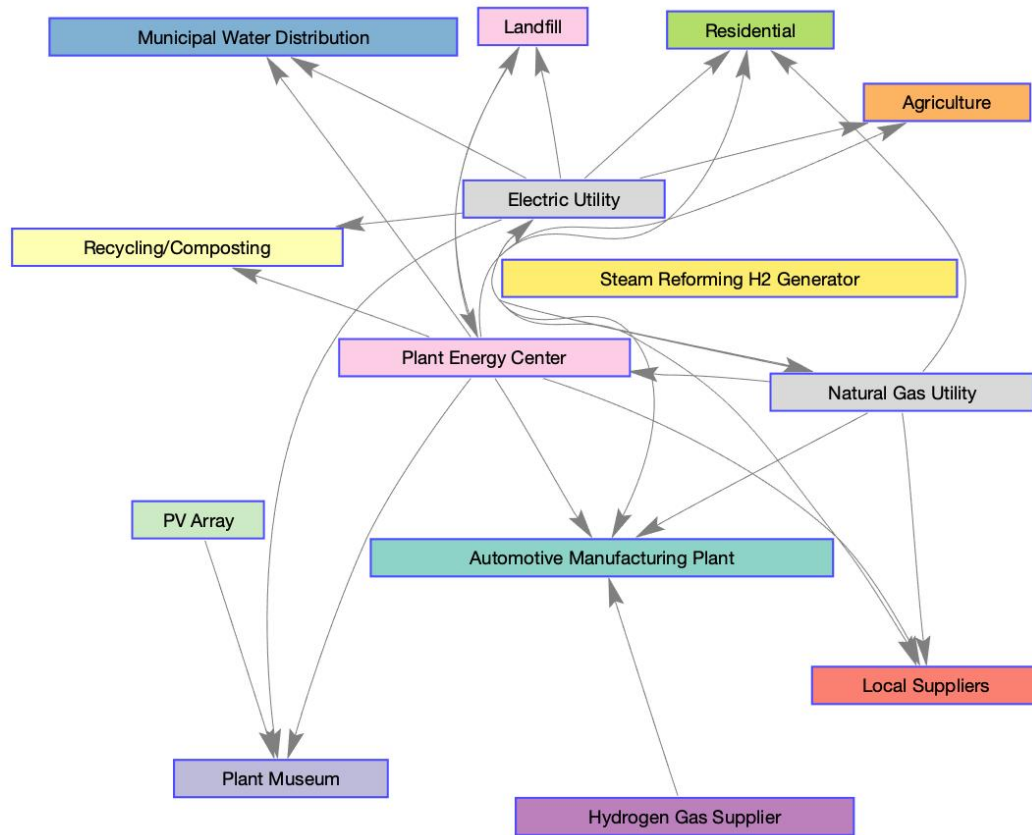


Figure 31. The Implementation of a Microgrid with the Surrounding Community in Energy Network Scenario Exploration of the Automotive Manufacturing Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).

This scenario would increase the diversity of power of the surrounding community, making the area around the manufacturing plant more like an ecosystem (from the point of view of primary and secondary consumers). In addition, this proposed system may improve the well-being of the community and the automobile manufacturer's relations with the city and its population, which includes some of its workers and its local suppliers/contractors.

Microgrids allow a small community (be it industrial or residential, or both) to self-sustain during power outages caused by grid maintenance, disasters or energy supply issues. This automobile manufacturer could make the excess electricity generation from the landfill-produced natural gas available to critical infrastructure in the local community such as police and fire stations, communication centers, hospitals, and gas stations. There is also an additional integration possibility within a 10-mile radius to include an airport that could serve the surrounding community during a disaster or other outage.

Beyond electricity, this scenario also explores how a shared hot water network would allow the automotive manufacturing facility to share hot water resources from the cogeneration equipment during a community-wide outage such as disruptions stemming from severe winter weather. Heating is a crucial resource during events such as these, especially in hospitals or for more vulnerable residents. A microgrid could be implemented in any manufacturing location but would most likely have the greatest impact in developing countries where the power infrastructure may be more unreliable. In addition, this energy would probably reach more people due to the energy use per capita is less in these countries when compared to the developed world.

Currently, the PV array on the automotive manufacturing museum provides a small amount of power to the museum itself. If the PV system were expanded, the array could contribute to the electricity needs of the manufacturing facility itself. This potential structural change is shown below in Figure 32.

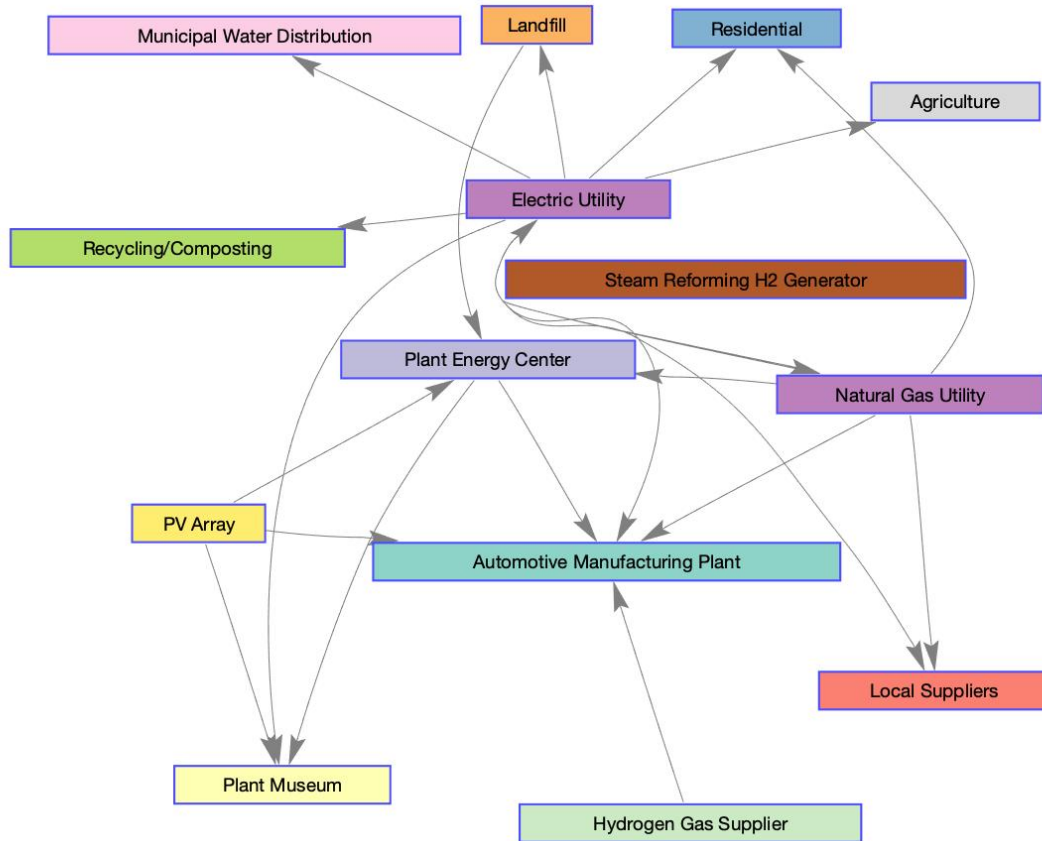


Figure 32. Expanded Solar Energy Generation Capacity Scenario Exploration in the Automotive Manufacturing Ecosystem. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).

In the event of a power outage, the PV system can support essential factory services along with the onsite landfill gas generators. If the automotive plant were to implement a microgrid setup with the surrounding community, the expanded PV array could also assist with external power loads. Although there are considerable capital costs involved in installing a PV array, the general infrastructure is established and maintenance is already required, meaning that expanding the existing PV array will be less resource intensive.

The final scenario combines all of the aforementioned energy ecosystem improvements to the automotive manufacturing facility to include an expanded PV array on the museum, hydrogen generation capabilities through steam reforming, a hydrogen fueling station, and microgrid capabilities. The resulting network structure is shown below in Figure 33.

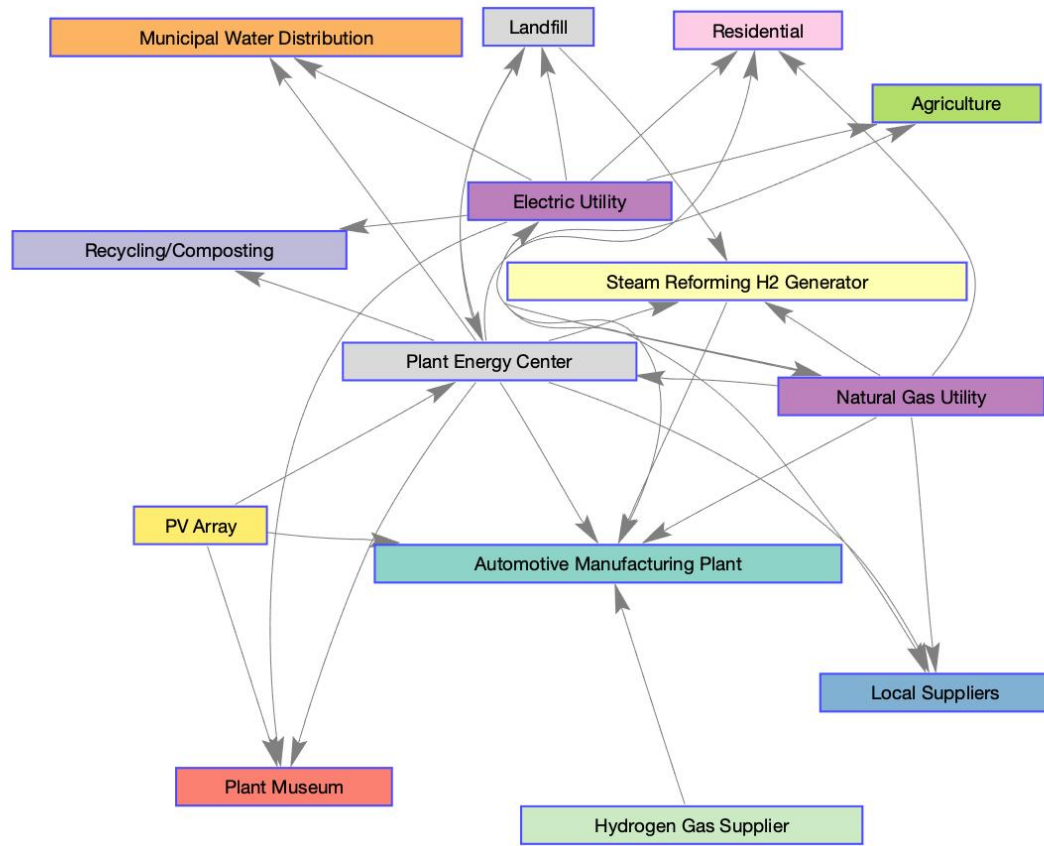


Figure 33. Combined "Best-Case" Structural Energy Network of the Automotive Manufacturing Ecosystem to Include an Expanded Solar Generation Capacity, Hydrogen Generation and Fueling, and Microgrid Capabilities. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).

The different energy network scenarios described above were evaluated using structural ecological metrics and the resulting values are given in Table 16 below.

Table 16. Energy Structural Ecological Network Results for the Automotive Manufacturing Ecosystem

	All	Hydrogen Generation	Microgrid Network	Hydrogen Generation Network	Solar Capacity Expansion	Current Energy Network
Linkage Density	2.27	1.67	1.67	1.53	1.40	1.27
Connectance	0.15	0.11	0.11	0.10	0.09	0.08

One can see that Linkage Density and Connectance have both increased substantially through scenario exploration, with the highest values resulting from the combination of all the scenarios.

5.4.6 Structural Combination of Water, Material, and Energy Networks

Step 4 of General ENA Modeling Methodology (ENAMM) from Figure 19 – Best Case Material/Water and Energy Structural Meta-Model

The next step for this analysis is to combine the best-case networks into a meta-model. First, we must look back to the scenario exploration for water, material, and energy to include all of the system components for this final structural meta-model model. We choose to include all the components in this meta-model because the combinations of scenarios proved to yield the highest individual ecological metric results in both Linkage Density and Connectance. However, the model connections between these components from the scenarios are not present. This combined meta-model is shown in Figure 34 below.

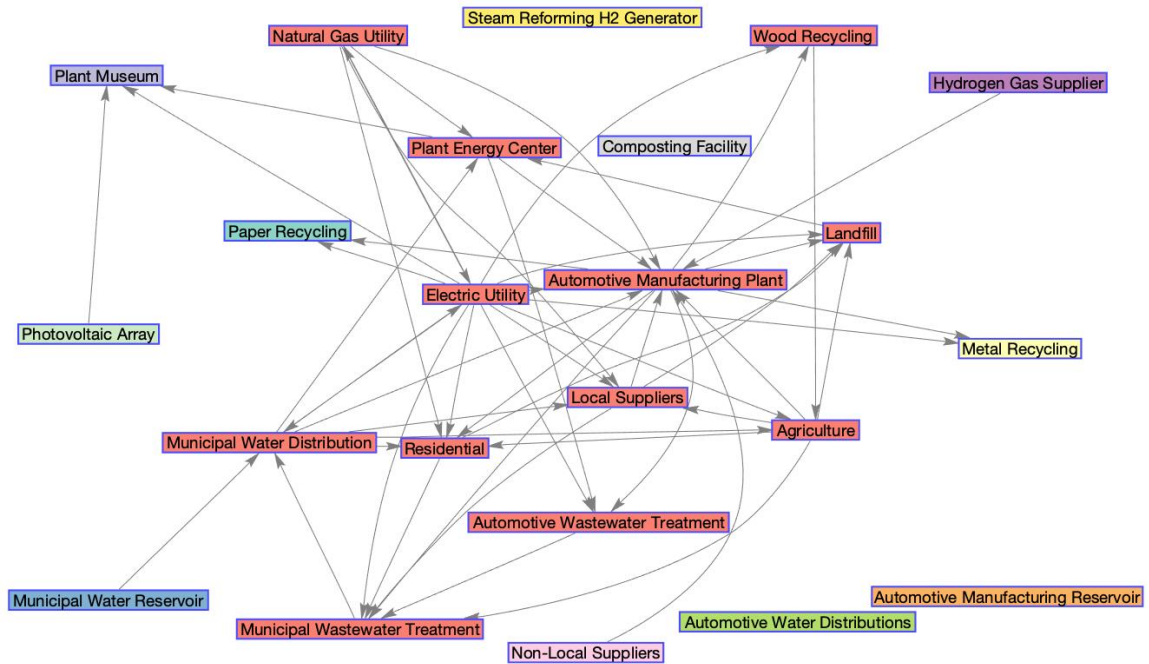


Figure 34. Original Combined Network Structure that Includes Materials, Water, and Energy Systems. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).

As one may observe, the network has many free-standing components that represent unutilized potential. Twelve of the twenty-three system components are strongly connected in the structural model.

Next, we include the connections between components from the best material, water, and energy scenarios. These connections are typically only due to the use of water or energy in components.

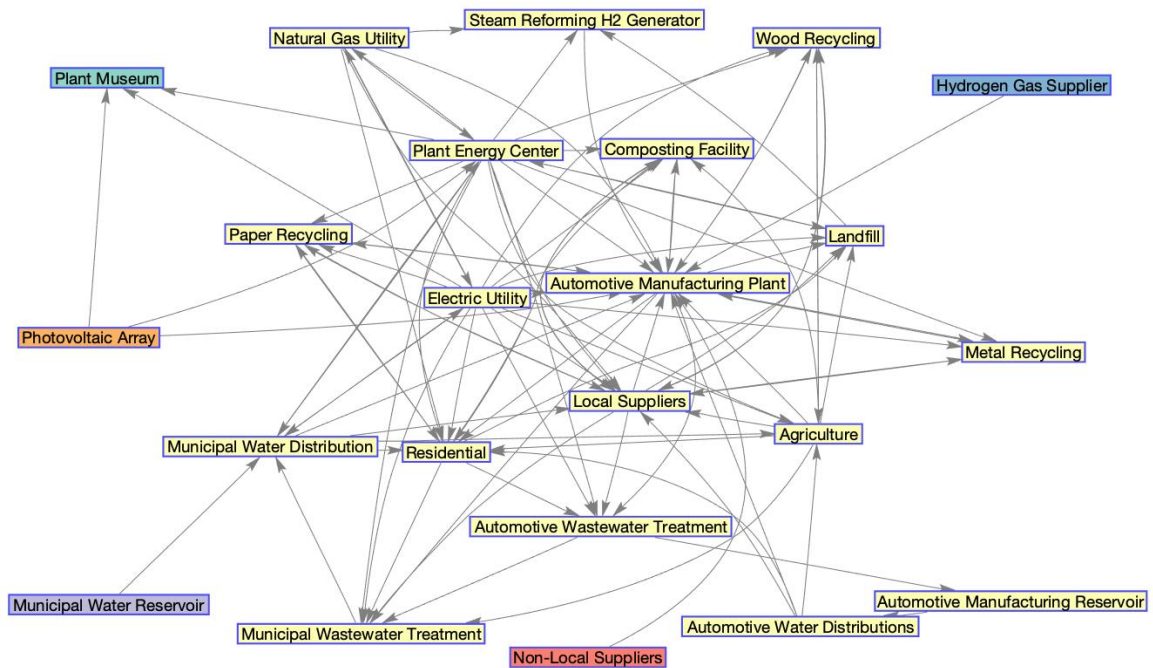


Figure 35. Best Combined Network Structure that Includes Materials, Water, and Energy Systems. Figure adapted from (Morris, 2020). System components of the same color are strongly connected, where components of their own color are not. A strongly connected node in a graph is defined as a subset of a networked system in which every node can be reached by every other node and the path will cycle back to the original node (Allesina et al., 2005).

As one may observe, the amount of strongly connected components (those components of the same color) increases tremendously from the original model to eighteen components of the twenty-three. Table 17 below shows the resulting structural ecological metric values for these combined networks.

Step 5 of General ENA Methodology (ENAMM) from Figure 19 – Structural ENA Metrics Calculated for Different Scenarios

Table 17. Structural Ecological Metrics Results for Combined Material, Water, and Energy Networks Meta-Model

	Best Case Network	Current Network
Linkage Density	4.13	2.17
Connectance	0.17	0.09

As one may observe, LD and C are both higher as a result of including the water, material, and energy interventions mentioned above. The automotive ecosystem now achieves and exceeds the LD recommendation of 3.54 presented in the generalized ENAMM from Figure 19. If in the best-case network, the results did not meet the recommended LD threshold, we should revisit the scenarios to explore more options for water, energy, and material waste stream interventions in an iterative manner until the threshold is met

This case study served as an example of steps 1-5 of our proposed generalized ENAMM from Figure 19. The goal of this study is to highlight the beginning stages of analyzing an engineered system by first assigning system boundaries. The case study then establishes initial high-level components, the connections of materials and energy, and determines the waste streams from these components. Then, this high-level model is refined to produce the initial water, material, and energy structural networks. Next, these structural models explore scenarios to incorporate biological, technological, or hybrid solutions to mitigate waste streams in the network. Finally, using the ecological structural metrics Linkage Density and Connectance, the best combination of these system components creates the structural meta-model of the automotive manufacturing ecosystem.

The structural analysis of engineered systems from an ecological perspective using ENA requires considerable thought and takes time to complete. Due to data limitations, this case study concludes with only a structural analysis. However, if this analysis were to continue, it would be suggested to now explore the feasibility of the proposed design before

presentation. However, this feasibility often is hard to determine without considering a flow-based analysis. This future analysis is outside the scope of the current study, although the next case study in Section 5.5 will explore the feasibility of designs of other engineered systems.

5.5 Case Study 2 – Carpet Manufacturing Model

In this case study, the proposed generalized ENAMM from Figure 19 begins at Step 6. The objective of this case study in the broader aspect of this dissertation is to highlight the latter stages of the modeling methodology to include flow value assignment, flow metrics calculation, and feasibility analysis that balances cost, environmental considerations, and ecological metric results. For a more in-depth explanation of the initial structural model development, scenario exploration, and meta-model structure, refer to (Guidry, 2008; Astrid Layton, 2016; Reap, 2009).

Step 6 of General ENA Modeling Methodology (ENAMM) from Figure 19 – Flow Network Construction

This case study uses data adapted from two studies that analyze a carpet recycling network model in Atlanta, Georgia (Astrid Layton, 2016; Reap, 2009). This particular carpet network is composed of 38 components – including one manufacturing facility, nine landfills, fifteen reuse and recycling facilities, and thirteen countries that consume carpet – with eighty-five potential material flows as shown below in Figure 36.

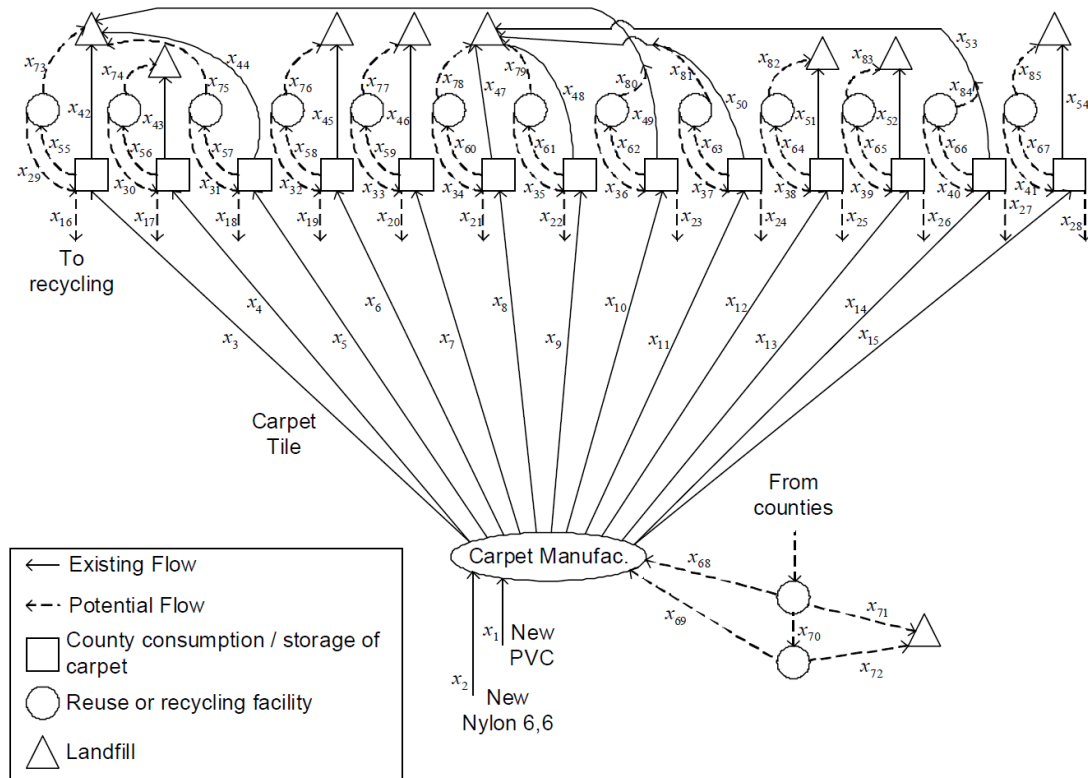


Figure 36. Carpet Material Recycling Network Model Developed by (Reap, 2009) and Adapted by (Astrid Layton, Bert Bras, & Marc Weissburg, 2016b)

This model's original structure has existing and pre-defined potential component links between the carpet manufacturer, counties in proximity to the manufacturer, recycling facilities, and landfills. New PVC and Nylon 6,6 enter the system where the carpet manufacturer produces carpet tiles. These tiles are then sent to one of Atlanta's 13 metropolitan counties (squares). The links between the carpet manufacturer and county in Figure 36 is not drawn to scale. The new carpet replaces old carpet that is then sent to one of eight landfills (triangles) or to a county's reuse and recycling facility (circles).

This choice between landfill or recycling creates the models twenty-six design variables when applied to the thirteen counties. Carpet exiting from the individual county's reuse and recycling facility's arrives at the first circle in the Figure 36 diagram where a

separation process yields the two major carpet tile constituents, PVC backing and Nylon 6,6. The PVC backing can be recycled in this first circle, where any Nylon 6,6 can then be sent to the circle below for recycling. The recycled materials are then sent back to manufacturing where they offset the need for new PVC and Nylon 6,6. As with most manufacturing, there are multiple constraints and operational parameters to consider in this carpet recycling model - a minimum demand that must be met to satisfy customers, a maximum supply of new materials from sources, maximum recycling rates, and costs associated with all flows. These minimum demand values for carpet material from Atlanta's metropolitan counties (PVC backing and Nylon 6,6) can be found in Table 18.

Table 18. Minimum Flow Constraints to Counties

<i>Actor</i>	<i>County</i>	<i>Minimum Material Requirement [kg/year]</i>
2	Cherokee	128,861
3	Clayton	214,779
4	Cobb	551,893
5	Coweta	81,015
6	DeKalb	604,666
7	Douglas	387,929
8	Fayette	82,875
9	Forsyth	89,440
10	Fulton	741,008
11	Gwinnett	534,364
12	Henry	108,372
13	Paulding	74,171
14	Rockdale	63,667

The other operational parameters and constraints needed for the model - the distances, efficiencies, costs (due to: manufacturing, material, labor, energy [electricity and natural gas], landfilling, recycling, cleaning), and emissions (due to: energy, transportation, manufacturing, cleaning, reuse), are adopted from (Reap, 2009).

In his work, (Reap, 2009) used two approaches to optimizing the carpet manufacturing and recycling network. The first used traditional performance metrics (i.e., cost and emissions) and the second used ENA metrics (i.e. Linkage Density, Finn's Cycling Index, etc.) to optimize the system with respect to reuse and recycling flows (i.e., x_i for $i=16, 17, \dots, 41$). The optimization algorithms adopted by (Reap, 2009) are provided in Table 19.

Table 19. Optimization Algorithms Adopted by (Reap, 2009)

Algorithm 1: Conventional Optimization Model (Z_{TRAD})		
Find:	x_i for $i = 16, 17, \dots, 41$	Carpet sent to recycling and reuse
Satisfy:	$\sum_{i=16}^{28} x_i \leq 915,761$ $x_{i+28} \leq 0.1r_i \text{ for } i = 1, 2, \dots, 13$ $x_i \geq 0 \text{ for } i = 1, 2, \dots, 85$	PVC recycling capacity constraint Reuse facility capacity constraint Positive flow constraint
Minimize:	C e	Total costs Total emissions
Algorithm 2: Bioinspired Optimization Model (Z_{BIO})		
Find:	x_i for $i = 16, 17, \dots, 41$	Carpet sent to recycling and reuse
Satisfy:	$\sum_{i=16}^{28} x_i \leq 915,761$ $x_{i+28} \leq 0.1r_i \text{ for } i = 1, 2, \dots, 13$ $x_i \geq 0 \text{ for } i = 1, 2, \dots, 85$	PVC recycling capacity constraint Reuse facility capacity constraint Positive flow constraint
Minimize:	P _S P _R	Specialized predator ratio Predator Ratio
Maximize:	LD C G V λ \overline{PL} FCI	Linkage density Connectance Generalization Vulnerability Cyclicality Mean Path Length Finn Cycling Index

All but three of the definitions for the ENA metrics shown in Table 19 can be found in this dissertation in Section 2.3.2. Cyclicality (λ) quantifies the amount of cycling in a structural

network and is based on the work of Dr. Brian Fath (B. D. Fath & Halnes, 2007). Specialized predator (P_s) ratio is the number of predators eating only one species divided by the total number of predators in the food web. The predator ratio (P_r) is the number of preys divided by the number of predators in a food web. These three metrics are not considered in this dissertation as they are either new or rarely found applied in ENA studies of ecosystems by ecologists.

Ultimately, Reap was unable to get his model to converge upon an optimal feasible solution using both a global gradient-based solver or a genetic algorithm solver, and instead adopted a Monte-Carlo based search algorithm to find 100,000 feasible points. He then selected the best objective function result that composed of equally weighted bio inspired (ENA) metrics. In this case study, we chose to approach this problem in a slightly different manner than Reap. Instead of nine metrics, this study focuses on three main objectives - 1) minimize system cost, 2) minimize emissions, and 3) maximize Finn's Cycling Index (FCI). System cost was chosen because it is a typically a dominating metric in decision making within the bidding process of engineered systems design. This cost metric includes energy, material, and transportation costs in the carpet manufacturing network. Emissions were included as an indicator of environmental performance and includes emissions from both transportation and those associated with material transformation (e.g., electricity use, and process emissions). The following sections shows the development of our optimization model.

5.5.1 *Multi-Objective Optimization for Economic, Environmental, and ENA*

Higher FCI values have been linked to reduced material and energy imports, resulting in decreased costs and waste generation (Astrid Layton et al., 2016b). Although Layton found that optimizing with ENA metrics – such as Average Path Length(\overline{PL}), Finn Cycling Index (FCI), or a combination – correlated well with optimization based on cost and emissions minimization, system costs are subject to change based on policy or market changes. Therefore, an assumption of this study is that by optimizing for cost, emissions, and FCI alone, other potentially important performance indicators (e.g., life cycle impacts) are neglected, potentially providing results that are environmentally or socially unfavorable.

The goal of multi-objective optimization is to develop the Pareto front or surface, in which no objective can be improved without hindering the other (Bokrantz & Fredriksson, 2017). Accordingly, this study uses the weighted-sum method as the architecture for this optimization problem as shown below in Table 20.

Table 20. The Weighted Sum Multi-Objective Optimization Method with Scalar Transformations

Algorithm 1: Weighted-sum method		
minimize:	$J(\mathbf{x}, \mathbf{p})$ $\mathbf{J} = [J_1(\mathbf{x}) \dots J_z(\mathbf{x})]^T$ $\mathbf{x} = [x_1 \dots x_n]^T$	J : objective function vector, with z objectives \mathbf{x} : design vector with n design variables \mathbf{p} : vector of fixed parameters
such that:	$\mathbf{g}(\mathbf{x}, \mathbf{p}) \leq 0$ $\mathbf{g} = [g_1(\mathbf{x}) \dots g_{m_1}(\mathbf{x})]^T$ $\mathbf{h}(\mathbf{x}, \mathbf{p}) = 0$ $\mathbf{h} = [h_1(\mathbf{x}) \dots h_{m_2}(\mathbf{x})]^T$	\mathbf{g} : m_1 inequality constraints \mathbf{h} : m_2 equality constraints
Scalar transformation:	$\min \tilde{J} = \sum_{i=1}^z \frac{\lambda_i}{sf_i} J_i$ $\sum_{i=1}^z \lambda_i = 1 \ \& \ \lambda_i \geq 0 \ \forall i$	\tilde{J} : aggregated sum of weighted objectives sf_i : scale factor λ_i : weight of the i -th objective
Specific objectives:	Minimize SC (x) Minimize EC (x) Maximize FCI	Total system costs Total emissions costs Finn Cycling Index

This method was chosen to develop our Pareto front because it was simple to understand and implement (Kim & De Weck, 2005). The weighted sum method is a popular approach in solving multiple objective non-linear systems because it minimizes the objective vector into a simple scalar; that is, this method solves a series of single-objective problems rather than one multiple objective problem (Kim & De Weck, 2005).

Our objective function follows a similar form to Table 20 above as shown below:

Minimize:

$$\begin{aligned} J(-FCI, TSC) &= \left(\frac{\lambda_1}{sf_1} \right) - FCI + \left(\frac{\lambda_2}{sf_2} \right) TSC \\ &= \left(\frac{\lambda_1}{\max(FCI)} \right) - FCI + \left(\frac{\lambda_2}{\max(SystemCost)} \right) TSC \end{aligned} \quad (1)$$

Where:

$$TSC = System\ Cost + Emissions\ Cost \quad (2)$$

$$Max(System\ Cost) = Given\ from\ (Reap, 2009) \quad (3)$$

Such That:

$$System\ Inputs = System\ Outputs \quad (4)$$

$$Exports(X) - Exports(X_0) \leq 0 \quad (5)$$

Our bi-objective function maximizes Finn Cycling Index while minimizing the total system costs (to include operational costs and emission costs). The objectives are scaled using upper bound values of 1 for Finn Cycling Index, and 5.9 million \$/year operation amounts supplied by Reap's study. The flow values in and out of the network should be balanced in accordance to the conservation of mass. Finally, the demands of the customers in the counties are met by the system output through exports (X) must be greater than or equal to the current production amount (X₀).

To compare our results to previous work and put our findings into context, we introduce a previous ENA optimization model applied to the same case study by Astrid Layton (2016). Z_{bio}, the biologically inspired objective function from Layton and Reap, was defined as:

$$Z_{bio} = d_{min} + d_{max} \quad (6)$$

$$d_{min} = w \left(1 - \frac{P_s}{G_{P_s}} \right) + w \left(1 - \frac{P_r}{G_{P_r}} \right) \quad (7)$$

$$w \left(1 - \frac{G_{LD}}{L_D} \right) + w \left(1 - \frac{G_G}{G} \right) + w \left(1 - \frac{G_V}{V} \right) + w \left(1 - \frac{G_\lambda}{\lambda} \right) + w \left(1 - \frac{G_{PL}}{PL} \right) + w \left(1 - \frac{G_{FCI}}{FCI} \right) \quad (8)$$

where P_s is the number of specialized predators, P_r is the prey to predator ratio, L_D is the linkage density, G is the generalization, V is the vulnerability, λ is the cyclicity, \overline{PL} is the average path length, FCI is the Finn Cycling Index, w is an assigned weight, and all G_x symbols are the goal values for those metrics. These goal values are shown below in the first column of Table 21. The goal values for LD (5.04) and FCI (0.295), the key structural and flow-based ecological metrics in this dissertation, are based on median Food Web ENA values (Astrid Layton, 2016). These proposed goal values slightly exceed the recommended values in our generalized ENAMM from Figure 19 (3.54 and 0.09 for LD and FCI respectively). However, the main objective of this section of our case study is to confirm and compare optimization results and a secondary goal is showing an example of setting an optimization target with ecological metrics and achieving results.

In addition to the ecological values, the traditional objective function calculated by Reap was calculated here and compared. Z_{trad} is calculated by

$$Z_{trad} = d_{cost} + d_{emissions} \quad (9)$$

$$d_{cost} = w \left(1 - \frac{C}{G_{cost}} \right) \quad (10)$$

$$\begin{aligned}
d_{emissions} = & w \left(1 - \frac{e_{CO2}}{G_{CO2}} \right) + w \left(1 - \frac{e_{CH4}}{G_{CH4}} \right) + w \left(1 - \frac{e_{N2O}}{G_{N2O}} \right) + w \left(1 - \frac{e_{SO2}}{G_{SO2}} \right) + w \left(1 - \frac{e_{NOx}}{G_{NOx}} \right) \quad (11) \\
& + w \left(1 - \frac{e_{Pb}}{G_{Pb}} \right) + w \left(1 - \frac{e_{CO}}{G_{CO}} \right) + w \left(1 - \frac{e_{VOCs}}{G_{VOCs}} \right) + w \left(1 - \frac{e_{Hg}}{G_{Hg}} \right) \\
& + w \left(1 - \frac{e_{HC}}{G_{HC}} \right) + w \left(1 - \frac{e_{PM}}{G_{PM}} \right) + w \left(1 - \frac{e_{SOx}}{G_{SOx}} \right)
\end{aligned}$$

where, C is cost, e_y are the emissions created for species y . All other values were previously defined.

Adapting the carpet manufacturing and recycling network parameters and constraints, we first compared our results with those of (Reap, 2009) and (Astrid Layton, 2016) in order to identify errors and validate our models behavior. We then performed optimization on our model using our multi-objective approach with cost, emissions, and FCI in order to compare outputs. Due to these fundamental changes in the models objective, we expect our results to differ from those of (Reap, 2009) and (Astrid Layton, 2016). The full extent of model development and MATLAB code can be found in APPENDIX C. Case Studies Supplemental Information.

5.5.2 Results and Discussion – Carpet Manufacturing Model Case Study

Step 7 of General ENA Modeling Methodology (ENAMM) from Figure 19 – Calculation of Flow Network Metrics for Scenarios

Combining the cost, emissions, and ENA objectives into one objective function for the optimization results in the network with improved ecological metrics across the board as shown below in Table 21 as compared to Reap and Layton.

Table 21. Objective Function results and ecological metric values from original carpet study as compared to the current study. Original metric values found in (Astrid Layton, 2016) and (Reap, 2009).

	<i>Food Web Goal Values</i>	<i>Layton (2016) Best Structure Values</i>	<i>Reap(2009) Best Z_{trad} Values</i>	<i>Current Study</i>
$Z_{bio}, G, P_s, P_r, \lambda$	-	0.513	0.53	0.37
Z_{trad}	-	0.263	0.2	0.953
Z_{val} (current study)	-	-	-	-0.225
n	51	24	29	29
L	249	45	46	56
n_{Prey}	41	24	29	29
$n_{Predator}$	38	24	29	29
LD	5.04	1.88	1.59	1.93
P_R	1	1.09	1	1
P_s	0.1	0.583	0.483	0.483
G	6.18	1.88	1.59	1.93
V	5.34	1.88	1.59	1.87
λ	4.24	2.7	2	2.74
C	0.152	0.078	0.055	0.066
FCI	0.295	0.168	0.156	0.274
PL	5.7	3.30	4.68	4.58
AMI	1.74	2.34	2.69	2.14
A ($\times 10^6$)	0.0181	19.4	-	19.9
DC ($\times 10^6$)	0.0395	40.6	-	43.2
ϕ ($\times 10^6$)	0.0207	4.55	-	23.4
$T_{..}$ ($\times 10^6$)	0.0109	8.28	-	9.27
AC	0.372	0.477	0.591	0.459

This deviation from the results from the other studies could be due to changing the optimization method from a Monte-Carlo based approach that (Reap, 2009) and (Astrid Layton, 2016) relied on, to a gradient-based solver that yields an overall more optimal result. In addition, Astrid Layton (2016)'s model used a two-stage approach that first optimizes structural metrics (λ , P_R , P_s , and G), then holding this optimized structure constant, optimizes flows based on traditional cost and emissions. Astrid Layton (2016)'s approach led to the overall network structure where the number of links was less ($n=24$) than this case study ($n=28$, after removing landfill components to match Reap's study).

However, she was able to achieve better ENA metric values than those found by Reap. In contrast, we found that without modifying the system structure, we could optimize our material flow amounts to obtain greater values of FCI, and LD as compared to these two previous studies.

Step 8 of General ENA Modeling Methodology (ENAMM) from Figure 19 – Feasibility Analysis

Figure 37 below shows the models relationship between total system cost, the objective functions, and FCI in our case study by varying weights to achieve a pareto front.

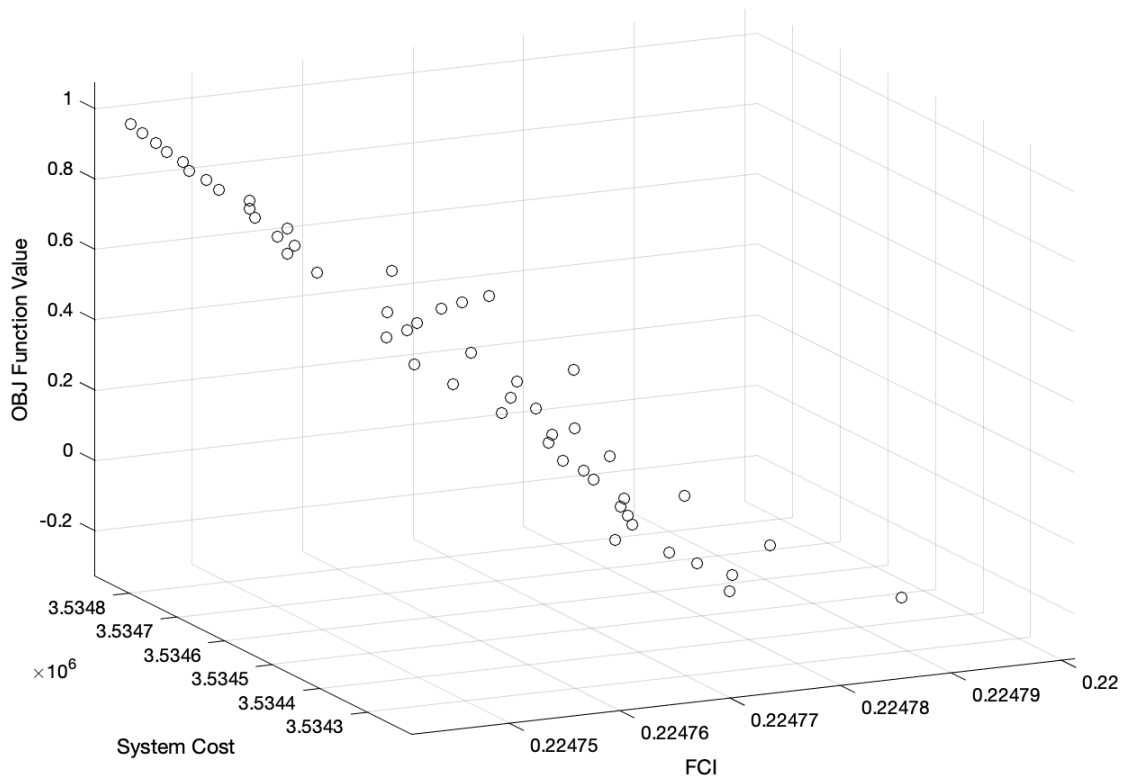


Figure 37. Pareto plot comparing two objectives (FCI and Total System Cost) with the objective function value.

Figure 37 shows as the objective function finds its minimum, system cost decreases as FCI increases. These results are similar to those found by Reap and Layton, however because our objective function only considered FCI (as opposed to the nine ENA metrics in Reap's model), this relationship between FCI and Total System Cost appears more pronounced.

Figure 38 below investigates this relationship further by examining our models FCI and Total System Cost through a linear model.

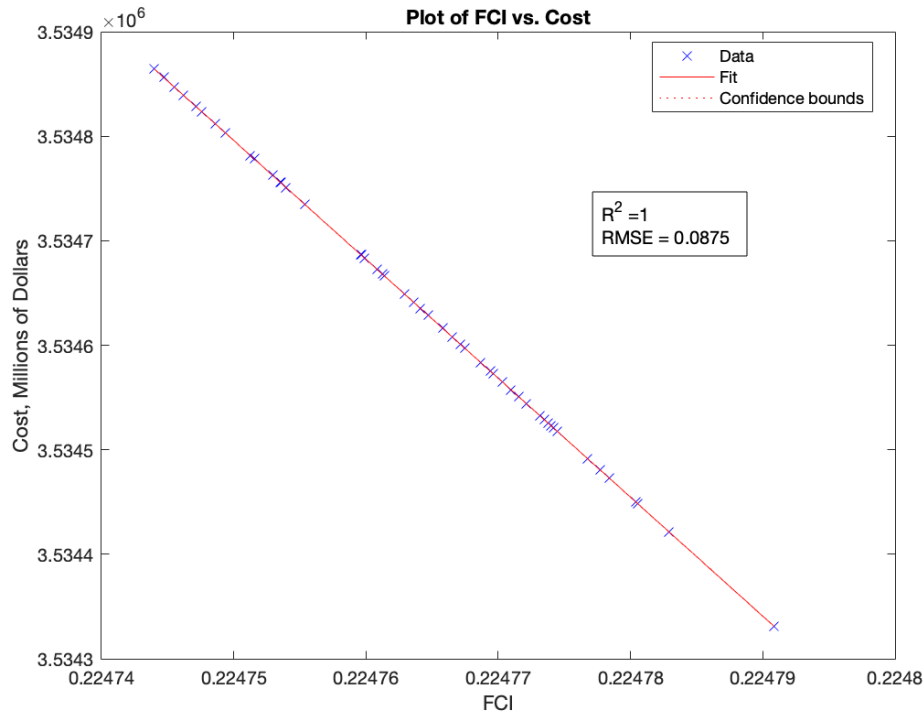


Figure 38. Linear regression of shows the FCI on the x-axis and the Total System Cost on the y-axis

This model shows a perfect fit with an R^2 value of 1 and a Root Mean Squared Error of 0.0875 and tight confidence interval. This result is not surprising, as in the carpet model, the cost to reuse or recycle carpet is less than that of producing carpet from new material. Therefore, more recycling should lead to less Total System Costs. Further, FCI is a measure of the total system cycled throughflow divided by the total system throughflow. This means, as recycling increases (and cost decreases), FCI increases as well. Since our objective function pushes to increase FCI as much as possible, these results make logical sense.

To examine this relationship further, below is the plot in Figure 39 of the residuals of the linear fit of FCI and Total System Cost.

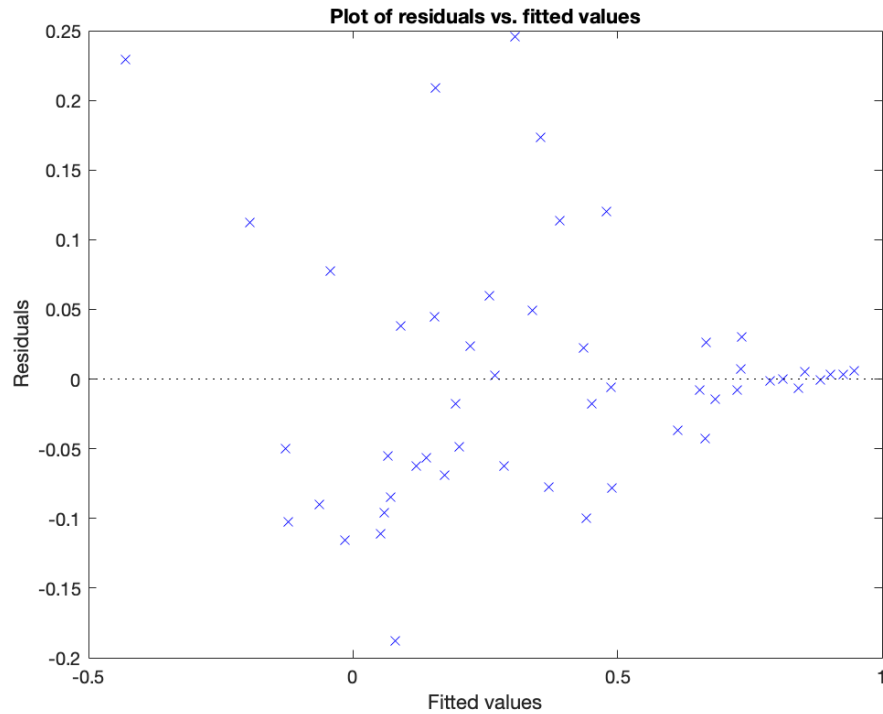


Figure 39. Residuals of linear fitted model shows the FCI on the x-axis and the total system costs on the y-axis

The residuals appear to follow a normal distribution. That is, there are a high density of points close to the origin and low density of points far from the origin. Furthermore, the points are symmetric about the origin. This adds validity to the original linear model assumption that errors are independent and normally distributed.

When creating a similar linear model for FCI and our objective function value, there is a less clear linear relationship as shown in Figure 40.

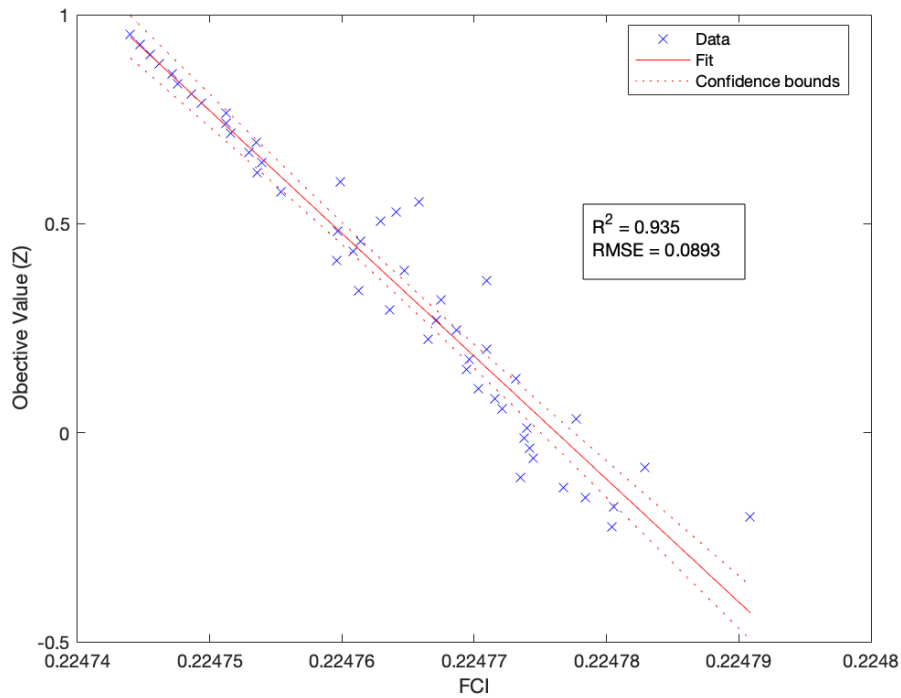


Figure 40. Linear fitted model of FCI vs the objective function value

The linear model of FCI and the objective function yields an R^2 value of 0.935 and a Root Mean Square Error of 0.0893, we show a much less linear relationship than that of FCI and Total System Cost. Many points lie outside of the 95% confidence interval as well. This suggests a linear model may not be the best fit, but to come to this conclusion we investigated the residual plot in Figure 47 below.

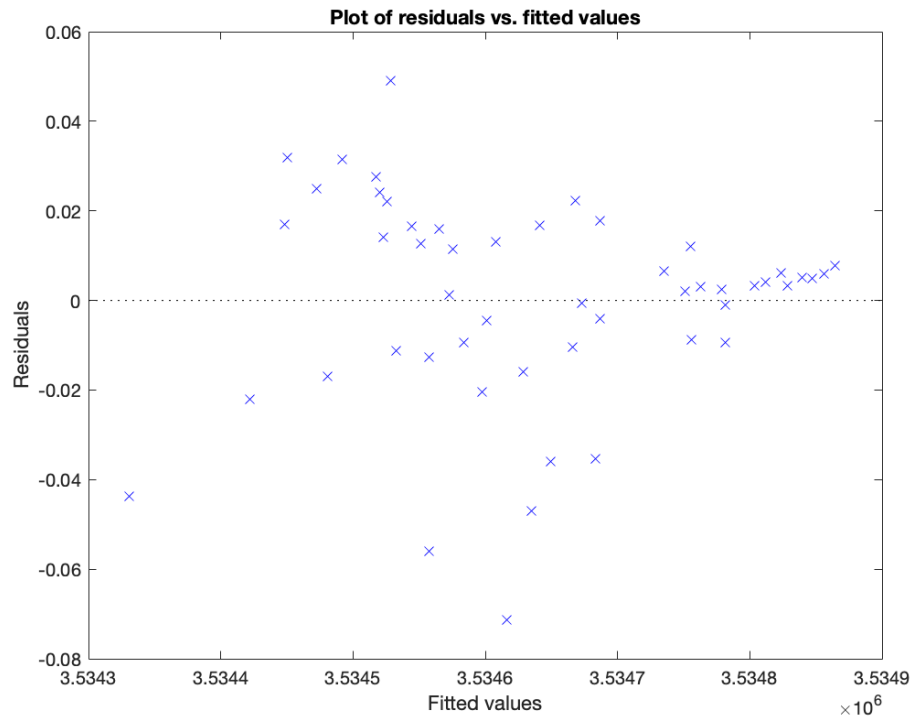


Figure 41. Residuals plot of the linear model of FCI vs objective function value

The residuals express less normal behavior than before in Figure 39. They are more condensed above the origin and skew far below the origin. Therefore, the distribution is not completely normal. However, it is clear from this that the relationship between FCI and the objective function is not completely linear but close, especially at lower FCI values.

The overall results from this analysis are clear that by bringing together the traditional optimization of cost and emissions with ecological metrics such as FCI from ENA, the final combined optimization results found a new optimum that yields better structure and flow metrics than those previously generated through Monte-Carlo simulation (Reap, 2009). Astrid Layton (2016)'s results suggest a two-stage approach to using ENA metrics in network construction and flow-assignment. They suggest a structural focused optimization followed by a flow-based optimization. We also agree this is a logical approach to using optimization and ENA metrics and it is recommend in our generalized

ENAMM from Figure 19 to address structural changes first before assigning flow-based values in a network.

5.5.3 *Conclusions*

The need is clear for a simple optimization tool for large-scale industrial and urban systems as shown in this study. Cost always is an obvious objective to minimize in engineered systems, but quantifying sustainability can be a harder target to achieve in practice. This approach brings together the traditional optimization of cost and emissions with these ecological metrics from ENA. The final combined optimization results were promising, as a new optimum for the ecological metrics was reached, yielding better structure and flow metrics than those previously generated through Monte-Carlo simulation (Reap, 2009). Similar to these previous studies, these results demonstrate that minimizing the costs and emissions and maximizing the ecological performance are not mutually exclusive. As cycling increases, the costs decrease, providing further support to the validity of applying ENA as an indicator for sustainable and traditional improvement.

Furthermore, the results from this and past studies demonstrate promise that ENA metrics may be able to model complex systems alone and still achieve similar or better model results that incorporate cost. This opens the possibility to circumnavigate the painstaking details needed to calculate costs required by conventional optimization strategies. This is beneficial because it reduces the amount of data needed to analyze these large and complex systems while still yielding both superior ecological performance and reduced cost. As this approach is further developed into a design tool with more facets of ENA, more information about the network will be given with the same input data allowing

designers to specify what is most important to them. With these developments, the tool will become a more robust tool for sustainable network design.

5.6 Conclusions

In this chapter, we provided the fundamental contribution of developing both a generalized model to describe engineered systems components and a quantitative methodological approach to analyzing a system of these components using ENA. We then provide examples of its implementation through two case studies. The first case study is of an automobile manufacturing facility and the second case study is of a carpet manufacturing recycling network. These studies highlighted what one might encounter while applying this proposed generalized and quantitative ENAMM.

In the first case study of an automobile manufacturing facility, the analysis considers simple structural modifications to improve its ecological metric values for the facilities energy, material, and water systems. This case study provides an in-depth analysis of the initial stages of the modeling approach – the underlying assumptions one might propose, the identification and establishment of system boundaries, and the identification of the correct level of coarseness when breaking the high-level systems down to the components inside system boundaries.

In the latter case study of a carpet manufacturing recycling model, we show a flow-based analysis following our generalized ENAMM. This case study describes less in initial model formulation, but highlights the later stages of the modeling approach that the automotive case study did not explore – the improvement of ecological metrics for these systems, the consideration of potential economic impacts brought about by this approach,

and one method for incorporating multi-objective optimization into the modeling process to balance cost and ecological metric improvements.

CHAPTER 6. BIOAUGMENTATION OF A STEEL WATER NETWORK USING CONSTRUCTED WETLANDS AND PYROLYSIS MODELING

In CHAPTER 5, we presented a generalized ENA Modeling Methodology (ENAMM) and applied it to two case studies from industry to maximize the fundamental ecological metrics LD and FCI found in CHAPTER 3 using the biological, technological, or hybrid waste stream interventions presented in CHAPTER 4. These two case studies from CHAPTER 5 examined in detail the application of ENAMM to the structural configurations of and flow-based configurations engineered systems separately. This chapter seeks to provide further context and validation to ENAMM by demonstrating a top-to-bottom analysis of an engineered system to include both the structural and flow-based analysis.

The current industrial production model meets population-driven demand in an unsustainable manner, generating vast amounts of environmental pollution and material waste that threatens global economic stability and changes Earth's climate. A key element to developing a more sustainable manufacturing model is efficient and effective resource utilization, a goal that mature biological systems achieve through the implementation of intricate decomposing networks. The objective of this work is to apply this biologically inspired logic to the design of industrial systems and model the resulting water, energy, and cost savings. We suggest this would contribute to the growing consensus that by leveraging the insight and utility of biological systems when applied to the established or

future manufacturing paradigm, designers may create more economical, resilient, and sustainable systems.

6.1 Research Questions to be Addressed

The following chapter provides a case study leading to the completion of Research Task 4 and supporting the Research Goals 1.5.1 and 1.5.2.

6.2 Background

Linear production has dominated the organization of manufacturing processes since the industrial revolution. This linear model involves the extraction of raw materials from the environment, the transport of these materials to manufacturing-heavy countries that create final products, the distribution and consumption of these products around the world, and finally the return of product remains to the environment as waste (Pearce, 1990). The combination of this manufacturing paradigm with dramatic population growth has resulted in unprecedented negative impacts to the natural world, which threatens the stability of global economies and survivability of humankind (Brundtland, 1987; Daily, 1997). Realizing these environmental problems, industry leaders, governments, and scientists alike have put forward frameworks to address industry practices in the sustainable use of natural resources (UNEP, 2000; United Nations, 1998, 2015). A significant portion of these frameworks focus on the sustainable uses of materials, water, and energy within the industrial realm.

One example of a linear production process in industry is Basic Oxygen Furnace (BOF) steelmaking, a process that produces steel from raw materials like coal, iron ore, and limestone. This BOF process, not to be confused with electric arc furnace steelmaking (producing steel from

melting scrap using electricity and commonly used in most western countries), is one of the most energy and emission intensive industries in the world. BOF steelmaking accounts for over 8% of annual global CO₂ emissions and China leads in global steel production (Allwood, Cullen, & Milford, 2010; Milford, Pauliuk, Allwood, & Muller, 2013). System Boundary & Initial Structure Development for Steel Manufacturing

Some scientists argue that the current high resource and energy demand of the Chinese Steel Industry (CSI) combined with the cumulative environmental degradation from years past, the CSI is currently unsustainable (C. Zhang & Wang, 2007). When evaluating this assertion, one cannot overlook the importance of the entire life cycle of the finished product. This importance stems from steel being the most recycled material in the world (Bureau of International Recycling Ferrous Division, 2015). Metals do not degrade due to recycling, thus the flows of materials exiting the steel manufacturing process and then being recycled later in the products life in the form of scrap is important as it's a potential source for feedback loops of material flows.

Step 1 of General ENA Modeling Methodology (ENAMM) from Figure 19 – Identify System Boundaries

Figure 42 illustrates the inputs of energy, water, raw materials, and scrap into the steel manufacturing process along with the other processes involved from the lifecycle of steel.

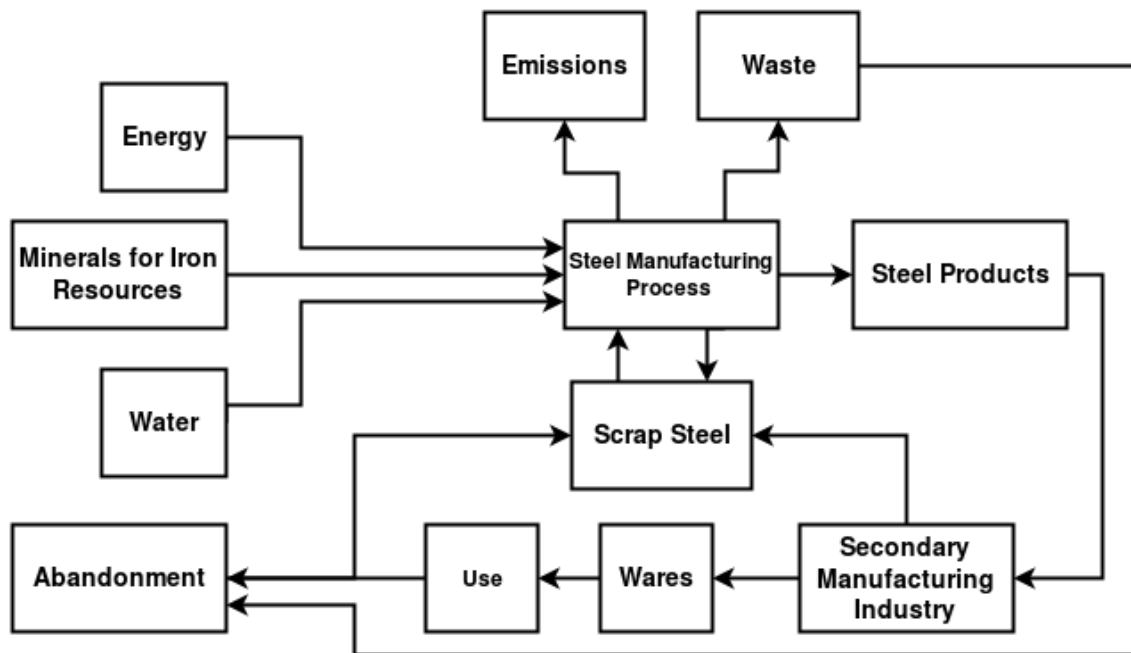


Figure 42. Life Cycle Flows of Steel

Understanding the full impact and uses outside of the system boundaries of the steel manufacturing process results in a more accurate analysis of the systems within the network and establishment of modeled system boundaries.

The raw material stores of BOF steel manufacturing consist of raw water, lime, coal, and iron ore. The main processes contributing flows within the BOF steel manufacturing network include the coking plant, sintering plant, lime plant, oxygen plant and water treatment plant. The core functions after these contributing flows include BF iron making, BOF steel making, and steel rolling/plate mills. Secondary processes that vary from plant to plant include types of hot metal pre-treatment, differing types of secondary metallurgy, and methods of reheating before the rolling or plate mills.

Step 2 and 6 of General ENA Modeling Methodology (ENAMM) from Figure 19 – High Level Component Breakdown and Flow Network Construction

In CHAPTER 5, we introduced our ENAMM that provided an 8-step method to analyze engineered systems using ENA. As mentioned, some of these steps may be combined when performing both a structural and flow-based analysis. We combine steps 2 and 6 to create a high-level component breakdown in our modeled steel manufacturing process and create the flow network at the same time with data from industry partners. The system boundaries of the modeled steel manufacturing process and the material flows that cross this boundary throughout the system can be defined as in Figure 43.

Byproduct gases are transported to boilers in the power plant to produce steam, which is then converted to electricity through turbines. We assume that byproduct gasses are also reused in the reheating furnace. This assumption is consistent with observations showing that in 2007, 90% of the BF's larger than 1000 m³ were equipped with a Top gas pressure Recovery Turbine (TRT). By the end of 2004, nearly 25% of the Chinese steel industry had Coke Dry Quenching (CDQ) units installed and in operation (International Energy Agency, 2007; L. Song & Liu, 2012). In addition, by the end of 2006, 77% of key Chinese steel enterprises had installed BFG recovery equipment and 64% had installed recovery equipment for other gas recovery such as Coke Oven Gas (COG) and Basic Oxygen Furnace Gas (BOFG) (L. Song & Liu, 2012). The assumptions for the current model are as follows:

- Due to the steel manufacturing fuel use being represented largely by coal, a conversion of off gases into coal equivalent is assumed
- Generation irregularities of byproduct gases are negligible which in reality, uncertainty factors such as equipment maintenance could affect the stable production of gases

The material flow amounts for the network shown in Figure 43 is provided below in Table 22 from our industry partner Anshan Steel Company in the People's Republic of China.

Table 22. Steel Water, Material, and Energy Flows in the Modeled Steel Manufacturing Network.

Flow From	Flow To	Amount	Units
Washery Coal	Coking Plant	1.2346	ton/ton-cs
Water	Cold Rolling Plant	0.2616	ton/ton-cs
Power Grid	Entire	0.0749	tce/ton-cs

Table 22. (Continued)

Water	Entire	4.8052	ton/ton-cs
Flue Emissions (Iron Plant)	Environment	0.0003	ton/ton-cs
Other Emissions (Steel Plant)	Environment	0.2983	ton/ton-cs
Other Emissions (Coking Plant)	Environment	0.849	ton/ton-cs
Dust Emissions (Coking Plant)	Environment	0.0009	ton/ton-cs
SO2 Emissions (Sinter Plant)	Environment	0.0422	ton/ton-cs
NOx Emissions (Coking Plant)	Environment	0.0016	ton/ton-cs
Effluent	Environment	0.13	ton/ton-cs
Con. Cast Slab (Steel Plant)	Hot Rolling Plant	0.56	ton/ton-cs
Water	Hot Rolling Plant	0.9249	ton/ton-cs
Pellet (Imported)	Iron Plant	0.3904	ton/ton-cs
Lump Ore (Imported)	Iron Plant	0.0981	ton/ton-cs
Coal (Imported)	Iron Plant	0.2019	ton/ton-cs
Sinter Ore	Iron Plant	1.2365	ton/ton-cs
Coke	Iron Plant	0.3173	ton/ton-cs
Oxygen Blast	Iron Plant	0.0171	tce/ton-cs
Water	Iron Plant	0.6722	ton/ton-cs
Lime & Dolomite Stone (Imported)	Lime Plant	0.13	ton/ton-cs
BFG	Lime Plant	0.0067	tce/ton-cs
COG	Lime Plant	0.0076	tce/ton-cs
Coke and Other Byproducts	Market	0.0036	ton/ton-cs
Wide & Heavy Plate Products	Market	0.2	ton/ton-cs
Cold Rolling Products	Market	0.1923	ton/ton-cs
Hot Rolled Plate Products	Market	0.4827	ton/ton-cs
COG	Outside Park Power Plant	0.0036	tce/ton-cs
BFG	Power Plant	0.0477	tce/ton-cs
BOFG	Power Plant	0.0289	tce/ton-cs
COG	Power Plant	0.0013	tce/ton-cs
Water	Power Plant	0.251	ton/ton-cs
Cold Rolling Scrap/Scale	Sinter Plant	0.0154	ton/ton-cs
Cold Rolling Scrap/Scale	Steel Plant	0.0023	ton/ton-cs
Hot Rolling Scrap/Scale	Steel Plant	0.0731	ton/ton-cs
Wide & Heavy Plate Scrap/Scale	Sinter Plant	0.041	ton/ton-cs
Wide & Heavy Plate Scrap/Scale	Steel Plant	0.0212	ton/ton-cs
Lime Plant	Sinter Plant	0.0635	ton/ton-cs

Table 22. (Continued)

Iron Ore Powder	Sinter Plant	0.9752	ton/ton-cs
Lime (Raw Material Yard)	Sinter Plant	0.0346	ton/ton-cs
Anthracite (Raw Material Yard)	Sinter Plant	0.0025	ton/ton-cs
Coke Powder	Sinter Plant	0.0538	ton/ton-cs
Water	Sinter Plant	0.0927	ton/ton-cs
Lime & Dolomite	Steel Plant	0.0808	ton/ton-cs
Oxygen	Steel Plant	0.026	tce/ton-cs
Hot Liquid Iron	Steel Plant	1.0096	ton/ton-cs
Water	Steel Plant	0.5666	ton/ton-cs
Other Emissions(Iron Plant)	Environment	1.863	ton/ton-cs
Crude Steel	To Plate, HR, and CR	1	ton/ton-cs
Water Treatment Plant Waste	Environment	3.6157	ton/ton-cs
Con. Cast Slab (Steel Plant)	Wide & Heavy Plate Plant	0.245	ton/ton-cs
Power Plant	Cold Rolling	0.0562	tce/ton-cs
Power Plant	Hot Rolling	0.0936	tce/ton-cs
Power Plant	Water Treatment	0.1788	tce/ton-cs
Power Plant	Wide and Heavy Plant	0.0318	tce/ton-cs
Power Plant	Oxygen Plant	0.0431	tce/ton-cs
Cold Rolling Plant	Water Treatment	0.3031	ton/ton-cs
Hot Rolling Plant	Water Treatment	0.76911	ton/ton-cs
Iron Plant	Water Treatment	0.0062	ton/ton-cs
Wide & Heavy Plate Plant Waste	Environment	0.0146	ton/ton-cs
Hot Rolling Plant Waste	Environment	0.2536	ton/ton-cs

The values shown in Table 22 show the simplified flows of material, water, and energy (in the form of coal equivalent) through the steel industrial meta-model. When ENA is applied to this meta-model, the following metrics are obtained and shown below in Table 23.

Table 23. ENA Metrics Results for the Current Steel Material and Water Network

	Linkage Density	Connectance	Finn Cycling Index	Average Path Length	Average Mutual Information	alpha
Steel Material and Water Meta-Model	2.7692	0.21302	0.1072	2.1014	1.2397	0.28445

The results shown in Table 23 indicate a highly efficient and connected model with a LD value of 2.77 and FCI value of 0.1072. This efficient structure is the result of hundreds of years of improvement on an industrial process to make it as efficient and profitable as possible. The current cycling in the network already achieves the value of 0.09 suggested by our ENAMM introduced in CHAPTER 5. However, improvement of the steel industrial model may still be obtained as the LD value falls short of the recommended value of 3.54 provided in our ENAMM. Therefore, we should explore scenarios to increase LD and FCI in our steel industry model by thoroughly examining the water, material, and energy flows in the network.

Step 3 of General ENA Modeling Methodology (ENAMM) from Figure 19 – Scenario Exploration

Previous research has compiled the material values in Table 22 and determined that water accounts for over 38% of total material flows in the steel network shown in Figure 43 (Stephen M. Malone, 2017). As such, it becomes apparent that apart from iron and energy, water is the most important commodity in steel manufacturing (American Iron and Steel Institute, 1999). Therefore, exploring the essential role of water in steel manufacturing and determining better structural or flow-based configurations in the water network could yield sizable environmental and economic returns.

In 2017, the Chinese Steel Industry (CSI) on average consumed 5.38 m³ of freshwater per kilogram of crude steel produced (China Iron and Steel Industry Association, 2017; World Steel Association, 2018). Most of this water use is due to

evaporation losses for cooling water. Therefore, reducing the amount of cooling water requiring traditional treatment and decreasing the amount of effluent generated from cooling could have major impacts in the overall amount of energy and water consumed by the steel manufacturing process. The major contaminants from cooling processes requiring removal prior to water recycling are chloride compounds and suspended solids. Without this treatment, the water is not suitable for processes that demand high quality water and could corrode mechanical equipment (Ma, 2012). Realizing the integral nature of water in the steel manufacturing process, this study seeks to provide an in-depth analysis of modeling and improving this water network.

6.2.1 Steel Manufacturing Water Network: A Production Process with High Resource Consumption and Emissions

Water demand contributes significantly to the cost of crude steel production, hence China has strategically repositioned the majority of their large manufacturing facilities along the coasts to provide freshwater through seawater desalination (X. Zheng, Chen, Wang, & Zhang, 2014). Over 68% of steel plants use Reverse Osmosis (RO) technology in the CSI, which consumes 13% of China's total desalinated water supply (Administration, 2018). RO treatment in the CSI does not remove monovalent ions such as chloride (Cl^-) efficiently leading to increasing concentrations as water is recycled throughout the system, particularly since water is evaporated during cooling processes (Greenlee, Lawler, Freeman, Marrot, & Moulin, 2009). The treatment of Cl^- is difficult due to its high solubility and typical water treatment technologies for Cl^- removal (RO, softening processes, and adsorption) are energy intensive and require substantial infrastructure investment. In addition to chlorides in the RO permeate cooling water, the Reverse

Osmosis Concentrate (ROC) generated from desalination contains many inorganic salts, heavy metals, anti-scalants, and coagulants that are typically discharged to the environment at great financial and environmental cost (Greenlee et al., 2009; Lattemann & Hopner, 2008). Therefore, determining the most effective means of cooling water and ROC treatment is essential to ensure the efficient and sustainable operations of the CSI. A more cyclic industrial process is required to meet the growing demand for steel production while reducing energy and material consumption particularly given the growing worldwide demand for goods.

6.2.2 *Biological Augmentation as a Possible Solution*

Biological systems may offer insight on how to efficiently transform materials from one form to another in natural and industrial settings. These systems have long been integrated into the chemical, agricultural, medical, and material industries (Drews, 2000; Langer & Tirrell, 2004; Weiland, 2010). For example, Constructed Wetlands (CW) are biological systems that use wetland vegetation, substrates, and their associated microbial assemblages to improve water quality and have been in use for over 50 years in the petrochemical, meat processing, dairy, and paper industries (Jan Vymazal, 2008; J. Vymazal, 2014). However, the adoption of this treatment method for wastewater in steel manufacturing is lacking despite research indicating positive results (Huang, Ling, Xu, Feng, & Li, 2011; Xu et al., 2009; Yang & Hu, 2005). This deficiency may be attributed to a lack of understanding regarding CW treatment methods and their implementation at scale, the emphasis of current CW research on heavy metal treatment rather than Cl^- removal, or a shortage of disposal options for the CW plants following treatment. Common biomass

disposal options include pyrolysis, composting, compaction, incineration, ashing, and liquid extraction (Sas-Nowosielska et al., 2004).

A cyclic system that operates similarly to natural ones would result not only recycle water but also would return plant biomass into the system to harvest the available energy, rather than transporting the biomass and its embedded energy off site. Biological systems retain and recycle nutrients and materials by implementing intricate decomposing networks, and previous research has found this type of functional role missing in industrial networks.(S. M. Malone et al., 2018) This functional deficit often is the driver of the performance gap in natural versus human systems.(Astrid Layton et al., 2016a, 2016b; A. Layton et al., 2016; S. M. Malone et al., 2018; Stephen M. Malone et al., 2018) As such, a disposal scenario that integrates the newly grown plant matter that removed Cl^- from the water streams back into the manufacturing process would mimic this decomposing function by preventing the exports of material and energy. Of the common disposal scenarios, pyrolysis is a simple process that is easily able to reintegrate the plant matter back into the steel making process as a value-added upcycled biochar. Therefore, the focus of this study is to investigate the ability of CW to produce both water and energy cycling by not only using plants to clean water but by incorporating the embedded energy of the plants into the steel manufacturing process via pyrolysis-driven biochar generation. This approach is illustrated in Figure 44.

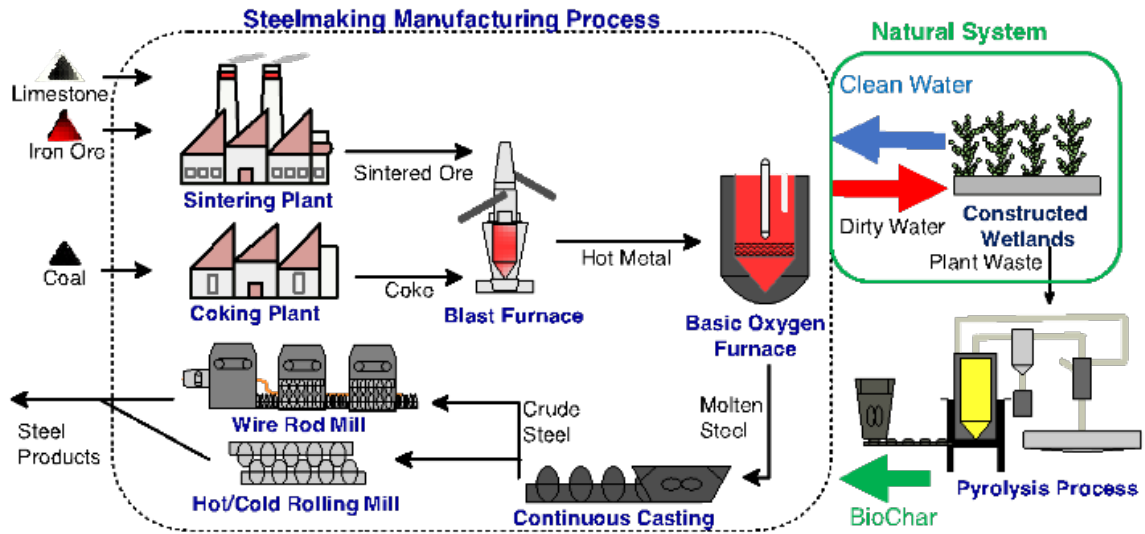


Figure 44. Illustration of using a combined constructed wetlands and pyrolysis process in basic oxygen furnace steel making

To these ends, this study explores an array of plant species found throughout literature to target and treat ROC and steel cooling water. We model the physical requirements and the integration of the wetlands into an existing steel park, examine the consequences of CW for material and energy cycling, and investigate the potential economic costs and environmental impacts of this approach.

6.3 Materials and Methods

6.3.1 Integration of Wetlands into the Water Network

The water network in steel manufacturing is complex, with many types of water systems feeding the various elements within the park at different rates. These systems exist in various configurations, such as closed- and open-cooling water systems and once-through water systems that serve different objectives such as water treatment and desalination. The figure in D.1 Steel Water Network shows the complete modeled

water network, however the network complexity distracts from the structure of how the individual water systems feed different park elements. Therefore, Figure 45 describes a simplified water network by removing self-recycling loops and combining duplicate edges between park elements.

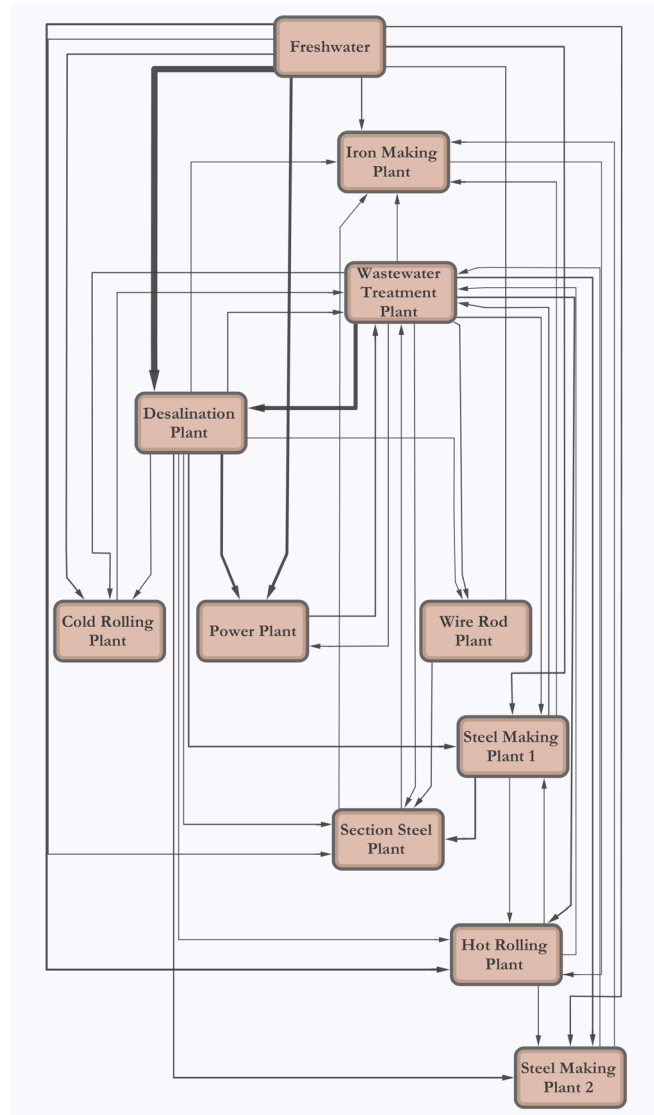


Figure 45. The simplified flows of water throughout a steel manufacturing park. The nodes (brown) represent major elements of the steel park. The weighted edges between these nodes are representative of flow magnitude ranging from $0.05 \text{ m}^3 \text{ hr}^{-1}$ to $43650 \text{ m}^3 \text{ hr}^{-1}$.

The brown nodes in Figure 45 represent the different elements found throughout the steel park, and the weight of the edges represent the flow magnitude. The structure, flow magnitude, and contaminant concentrations of the water network were acquired from our industry partners Anshan Steel Company in the Liaoning Province of the People's Republic of China. An optimization of this water network was presented in a previous study (X. Zheng et al., 2014).

As mentioned, the ROC and recycled cooling water from the desalination systems are the two designed inputs into the constructed wetlands. The wetlands' Cl^- uptake, water quality of effluent, and available land area limits the flowrates of ROC and recycled cooling water into the wetlands. The plant species dictates the Cl^- uptake, and $100 \text{ mg L}^{-1} \text{ Cl}^-$ is the constraint set on the wetlands effluent (The upper limit of the modeled freshwater source concentration), and $746,260 \text{ m}^2$ is the assumed available area for the wetlands near a steel manufacturing facility provided by our industry partners. The major elements that require freshwater in the steel park may use the wetlands effluent after treatment, as the water quality would be that of freshwater sources. A previously built optimization model will be used to assess the impact on freshwater usage with and without the addition of wetlands. (X. Zheng et al., 2014)

6.3.2 *Plant Species Selection*

The desired result from this study is the removal of Cl^- from a mixed stream of ROC and recycled cooling water from the desalination systems by integrating CWs as material cycling loops, decreasing material and energy consumption. With this goal in mind, halophytic plants are natural candidates for exploration in the removal of Cl^- , as they

specialize in the long-term uptake and storage of salts from soils and water without significant damage to metabolic function.(Flowers, 1985) This salinity tolerance is an important factor in the model formulation, as the desalination ROC and recycled cooling water influent into the wetland have a high assumed static concentration of 800 mg L⁻¹ and 400 mg L⁻¹ of Cl⁻, respectively. The non-halophytic plant species included in this study serve as potential alternatives and validation for the selection of halophiles in the remediation of Cl⁻. Factors such as varying growth rates, accumulation rates of Cl⁻, experimental and growing conditions of each plant species, and availability of data in literature have limited this study to the seven plants shown in Table 24.

Table 24. Plant species selection with sources from literature. The data source row lists the publication source from literature. The data source notes row describes location/scenario of the data used in this study found within these sources



			
	Curators Herbarium (2017)	Missouri Botanical Garden	Seregin A.P. (Ed.) (1929)
Scientific Name	<i>Salicornia europaea</i> ^{a,c} (Glasswort)	<i>Climacoptera crassa</i> or <i>Salsola crassa</i> ^{a,c}	<i>Bienertia cycloptera</i> ^a
Growing Method	H.S.S.F.C.W. ^b	H.S.S.F.C.W. ^b	H.S.S.F.C.W. ^b
Data Source	Farzi, Borghei, and Vossoughi (2017)	Farzi et al. (2017)	Farzi et al. (2017)
Growth Rate (g m ⁻² d ⁻¹)	9.81 ± 0.55	10.94 ± 0.67	11.14 ± 0.58

Table 24. (Continued)

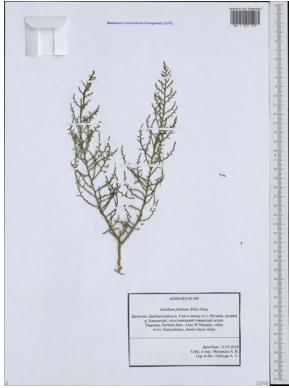
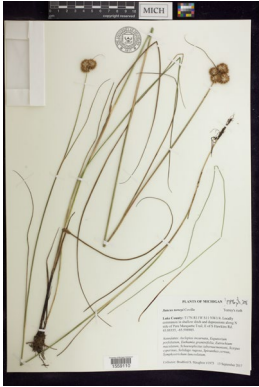

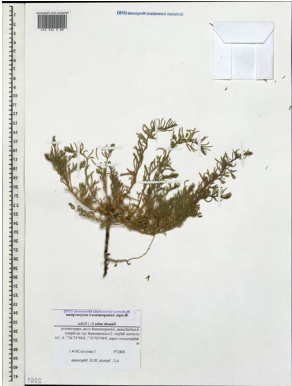
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	Seregin A.P. (Ed.) (2018)	Bradford S. Slaughter (2018)	Mark Whitten (2017)
Scientific Name	<i>Kalidium folium</i> or <i>Kalidium foliatum</i> ^{a,c}	<i>Juncus torreyi</i> (Torrey's rush)	<i>Typha latifolia</i> ^c (Cooper's reed, Cattail)
Growing Method	Soil in plastic pots	H.S.S.F.C.W. ^b	H.S.S.F.C.W. ^b
Data Source	Zhao et al. (2005)	E. R. Rozema, R. J. Gordon, and Y. B. Zheng (2016)	E. R. Rozema et al. (2016)
Growth Rate^d	14.50 ± 0.07	36.36 ± 0.11	29.71 ± 0.80
(g m⁻²d⁻¹)			
<hr/>			

Table 24. (Continued)

	
Seregin A.P. (Ed.) (2019)	
Scientific Name	<i>Suaeda salsa</i> ^{a,c} (Seepweed)
Growing Method	Soil in plastic pots
Data Source	Zhao et al. (2005)
Growth Rate^d	12.83 ± .05
(g m⁻²d⁻¹)	

^a Halophytic plant species

^b H.S.S.F.C.W. stands for Horizontal Subsurface Flow Constructed Wetlands

^c Native to China

^d Calculated based on the published information in each study

Table 24 references the studies used for the derivation of a universal parameter that describes the uptake of Cl⁻ per unit area and time. This universal parameter facilitates direct comparisons across these species given the capacity of plant-based systems to remove Cl⁻ is a function of plant growth rate, uptake rate per unit biomass, and total biomass over the

growing period. Figure 46 simplifies the in-depth information found in the studies presented in Table 24 to clearly observe the best performing plant species for this study.

The supplemental section

D.2 Universal Parameter Calculation provides detailed calculations of these parameters from the selected studies.

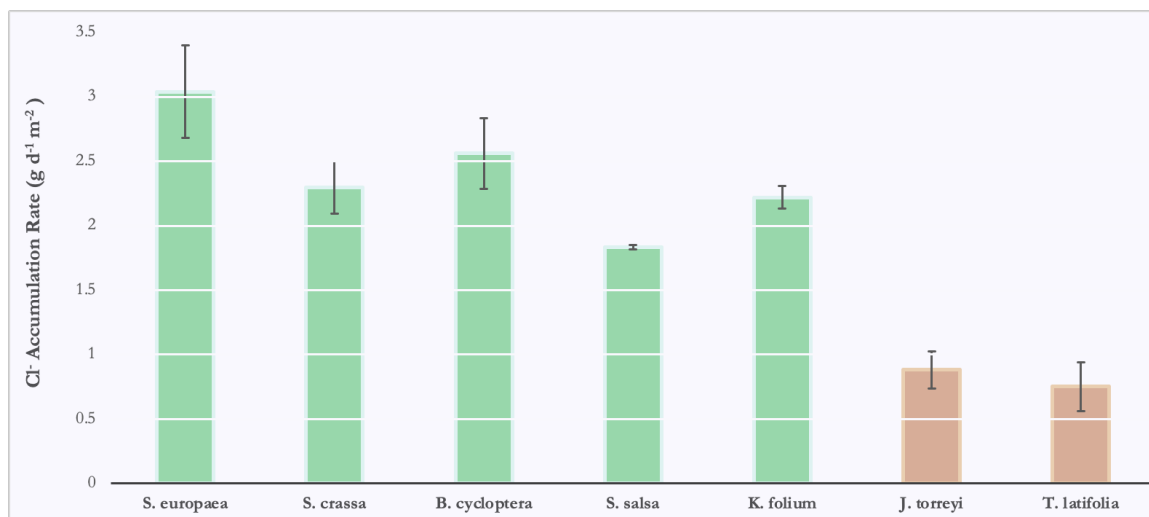


Figure 46. Chloride accumulation rate ($\text{g d}^{-1} \text{m}^{-2}$) of several plant species from various sources in literature. The five green bars represent halophytic plants, where the two brown bars are non-halophytic plant species. The vertical bars represent the mean value \pm the propagated standard error from the respective studies.

One may observe the dominance of halophytes (green) in Figure 46 in their ability to accumulate Cl^- as compared to non-halophytic plant species (brown). *J. torreyi* is the highest accumulating non-halophytic plant and has a growth rate of $36.36 \text{ g m}^2 \text{ d}^{-1}$. The highest accumulating halophytic plant, *S. europaea* accumulates over 3 times the amount of Cl^- as *J. torreyi* despite its growth rate ($9.81 \text{ g m}^2 \text{ d}^{-1}$) being the smallest of the plant species examined in this study. This finding demonstrates the importance of plant species selection in the design of contaminant specific constructed wetlands and that Cl^- uptake is not always driven by growth rate as opposed to biomass specific uptake rates. Though *S. europaea* is the highest Cl^- accumulator in this study and is the plant species of choice moving forward in this analysis, it is important to note that there are a number of candidate

halophytes that have been found to have similar or higher salt remediation capabilities, yet the studies of these plants lacked the comprehensive data necessary to calculate the uptake parameter used in this study.(Hasanuzzaman et al., 2014)

6.4 Pyrolysis as an End Use of Plants After Growing Period

Typical disposal scenarios for constructed wetland plants include landfilling, incineration, composting, compaction, and pyrolysis.(Sas-Nowosielska et al., 2004) Of these scenarios, pyrolysis is the only mechanism for disposal that allows for the reintegration of biomass waste into the steel manufacturing process. Pyrolysis is the thermal decomposition of biomass into a heterogeneous gas, liquid, and solid intermediate in an endothermic reaction. The solid product from the pyrolysis of biomass, sometimes referred to as “biochar,” is chemically analogous to charcoal and could thus supplement the coal consumption of the integrated steel manufacturing process. In order to formulate a predictive model to estimate the total coal material offset that could be achieved by integrating pyrolysis into the proposed biologically-inspired intervention, this study combines thermogravimetric decomposition data and rate kinetics from literature to approximate the amount of biochar and gas that would result from the pyrolysis of the constructed wetland plants. Finally, the total char yield and biomass growth is used to approximate the coal supplement that the wetlands may provide to the steel manufacturing process.

The thermogravimetric data used in this study originates from Dzidzienyo, Bastidas-Oyanedel, and Schmidt (2018) with a constant heating rate scenario of 5 K min^{-1} . The heating rate of 5 K min^{-1} is chosen over the higher heating rates in order to maximize

char yield.(Basu, 2013) Dzidzienyo et al. (2018) examined the thermal decomposition of *Salicornia bigelovii*, a plant within the same genus as *Salicornia europaea* but distinguished by growing region. Given the similarity of these plants, and lack of thermal decomposition data for *S. europaea*, it is assumed that *S. bigelovii* has similar thermal decomposition behavior. The experimental data from Dzidzienyo et al. (2018) is then used to approximate the char and gas yield using a reaction scheme developed by Koufopoulos, Maschio, and Lucchesi (1989) Figure 47 demonstrates this reaction scheme.

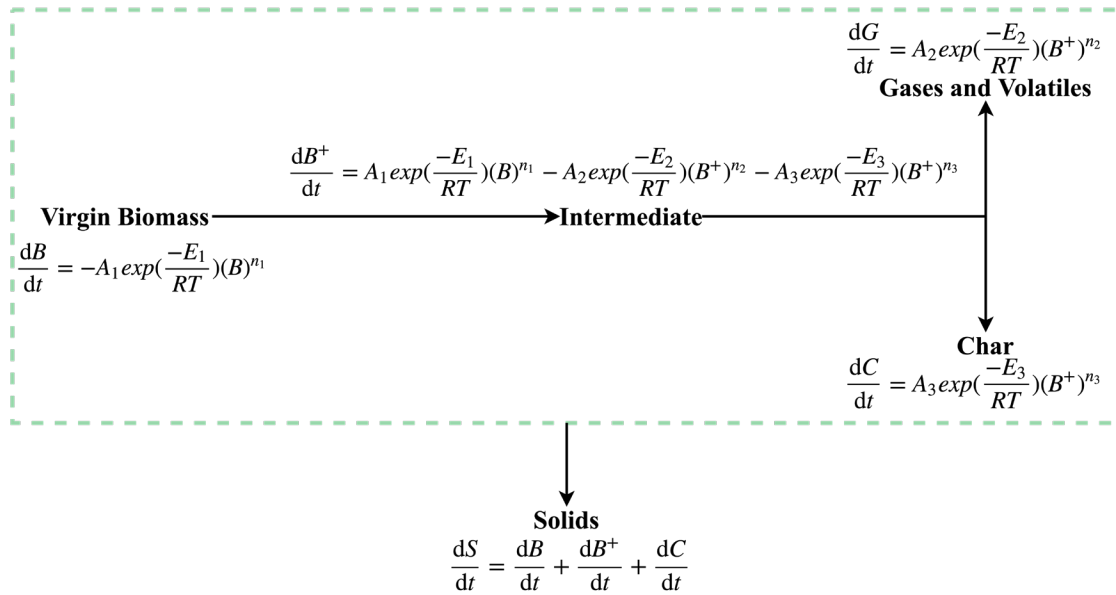


Figure 47. The pyrolysis reaction kinetics used in this study. The modeled change of solids over time during pyrolysis is the sum of biomass, intermediate, and char.

Intermediate product forms when weight loss of heated virgin biomass begins, which then further decomposes to char and gaseous products via two competing reactions. All reactions are assumed to follow the Arrhenius law and because thermogravimetric data is used, it is also assumed temperature follows a linear relationship with time via a constant

heating rate.(Dzidzienyo et al., 2018; Koufopoulos et al., 1989) The equations are solved numerically as an initial value problem using a fourth order Runge-Kutta approximation to the set of ordinary differential equations shown in Figure 47. Manipulation of the numerical approximation parameters provides estimations for the curve fitting of the modeled solids curve to the thermogravimetric data. A Quasi-Newton optimization routine fits the model to the experimental data by minimizing the sum of the squared residuals. The supplemental information found in D.3 Initial Parameters for Pyrolysis Model provides additional details of the calculation, initial values, and final parameter values. Finally, an assumed 5 million metric ton crude steel annual output and a 1.01 million metric ton annual coal demand provides the prediction of the coal offset by the constructed wetlands.

6.5 Results and Discussion

6.5.1 *Integration of Wetlands into the Water Network*

Figure 48 shows the changes to the original water network structure shown in Figure 45 with the addition of the wetlands.

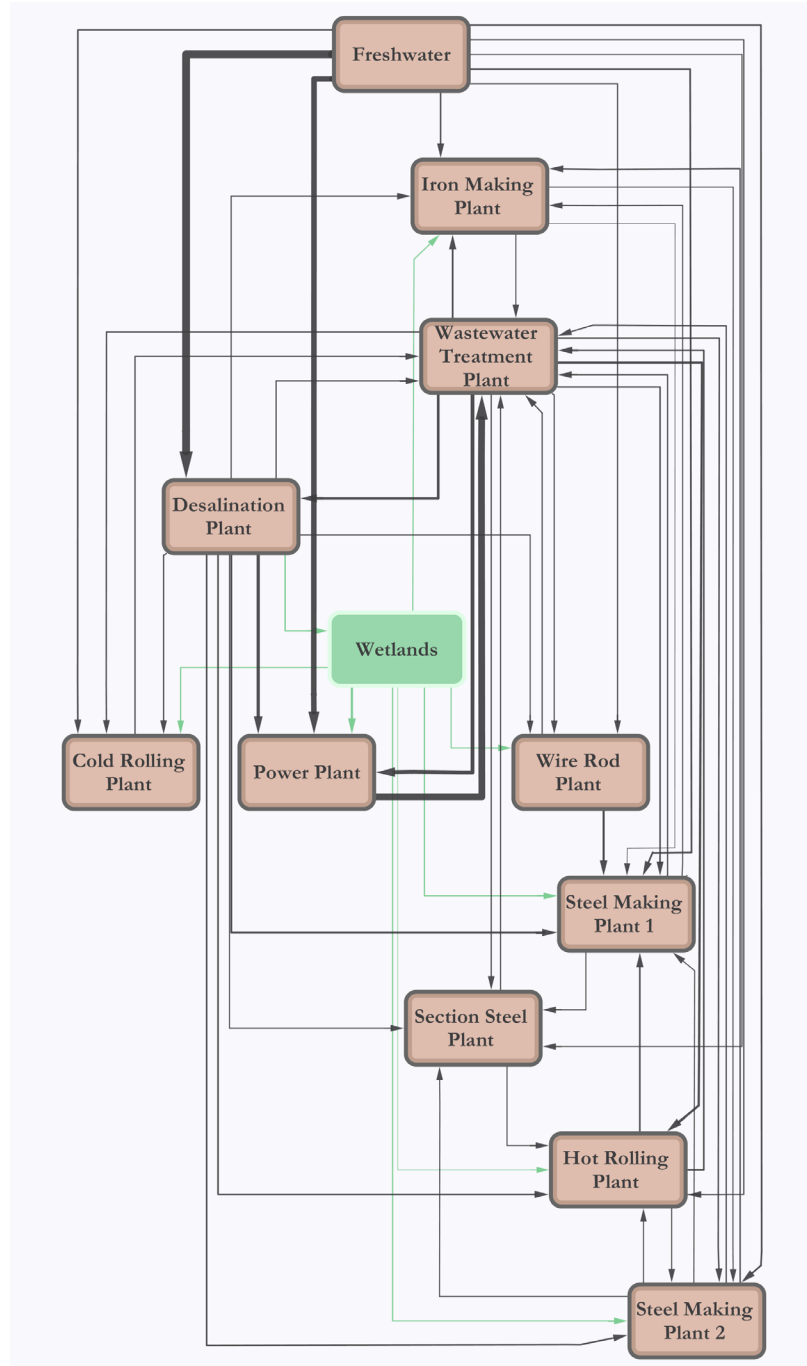


Figure 48. The simplified flows of water in a steel manufacturing park to the addition of constructed wetlands. The nodes in brown represent major elements in the steel park, while the weighted edges between these nodes are representative of flow magnitude ranging from $0.13 \text{ m}^3 \text{ hr}^{-1}$ to $43650 \text{ m}^3 \text{ hr}^{-1}$. The green node and edges shown in this figure represent the flows that differ from the original steel manufacturing network shown in Figure 45.

The edges highlighted green in Figure 48 demonstrate new flows generated from the inclusion of the constructed wetlands. The calculated influent flowrates to the wetlands are $110 \text{ m}^3 \text{ hr}^{-1}$ for ROC and $58 \text{ m}^3 \text{ hr}^{-1}$ for cooling water with a total wetland area requirement of $746,260 \text{ m}^2$. The plant biomass generated in this area is 4700 kg of dry weight per day and the water recycling rate of the steel water network increased substantially, which led to a decreased freshwater consumption rate of $6129 \text{ m}^3 \text{ hr}^{-1}$ to $3034 \text{ m}^3 \text{ hr}^{-1}$. In addition, a $99 \text{ mg Cl}^- \text{ L}^{-1}$ wetland effluent allows for the use of the wetland treated water throughout the manufacturing park for processes requiring the water quality of that found in freshwater sources.

These changes presented in Figure 48 have considerable impacts on the steel industry water network's ENA metrics. These changes are shown below in Table 25.

Step 5 of General ENA Methodology (ENAMM) from Figure 19 – Structural ENA Metrics Calculated for Different Scenarios

Table 25. ENA structure and flow results for the steel industry water network

	LD	C	AC	AMI	FCI
Original Model	3.00	0.2727	0.27109	1.2747	0.11276
Model with Wetlands	4.18	0.3802	0.2332	1.1747	0.18511

As one may observe, the original model shown in Figure 45 had a LD value of 3 with an FCI value of 0.113. The FCI value of this original model falls within the suggested values of our ENAMM (FCI of 0.9 in ENAMM), but the LD value of this original model falls short (LD of 3.54 in ENAMM). However, with the inclusion of the constructed wetlands as a biological “decomposer” in place of traditional water treatment as shown in Figure 48, we were able to raise this LD value to 4.18 and elevate the FCI value to 0.185. These results

are expected due to the higher density of connections but also due to the revised magnitude of flows in the network. The higher density of connections is due to the fact that the freshwater generated by the wetlands achieves a quality of water that can be used in any of the steel manufacturing water demand processes.

Figure 49 below provides insight to some of the major flow magnitude changes between model scenarios. The figure compares the original model flowrates from K. L. Zhang et al. (2018) (on the y-axis), to the model with the constructed wetlands (x-axis) presented in this study. Any points on the line represent flows that are equal in magnitude, where the points (flows) above the line represent a higher flow magnitude in the original model as compared to the model with the constructed wetlands. Similarly, any flows beneath the line represent flows that increased in magnitude in the wetlands model from the original model.

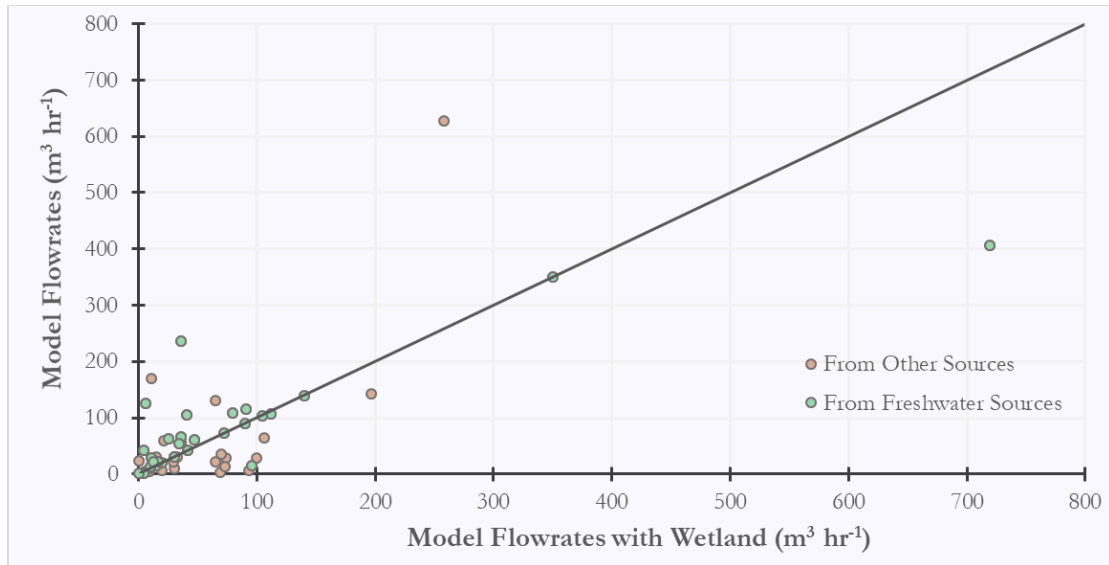


Figure 49. Flowrate changes from the original model to the model incorporating the wetlands. The green points represent flows originating from freshwater sources, where the brown dots are flows originating from other elements in the steel manufacturing water network. This figure excludes flows greater than $800 \text{ m}^3 \text{ hr}^{-1}$ and flows that differ structurally.

The points in green represent flows from freshwater sources (Freshwater from local streams/rivers or treated water from the on-site wastewater treatment plant), and the points in brown represent flows between other network elements. As one may observe, the freshwater sources appear to either remain the same (on the 1:1 line) or decrease.

While the overall freshwater consumption decreases, the freshwater and wastewater treatment plant flows to and from the powerplant increase by nearly six times from the original model to the model incorporating the wetlands. In addition, wetlands flow accompanies this freshwater increase to the powerplant. The powerplant then sends its wastewater to the treatment plant, which then sends much of the water directly back to the powerplant. This indicates most of the economic return in the optimization of the wetlands model lies with the combined flow of freshwater and wetlands water between the powerplant and wastewater treatment plant. The higher utilization rate of the powerplant

water exchange in this study agrees with other studies that utilize optimization and process integration in similar integrated steelmaking water networks, suggesting a growing consensus and warranting further investigation in the pursuit of freshwater savings.(Tian, Zhou, & Lv, 2008) Moreover, the decrease found in this study (50%) is similar to that found by Tian et al. (2008), where over 57% of freshwater use could be reduced in a Chinese integrated steel plant water network via the integration of water-using processes and optimization using a nearest neighbor algorithm to restructure the water network.

6.5.2 End Use of Plants After Growing Period

Figure 50 shows the results of the pyrolysis model shown in Figure 47 applied to the thermogravimetric data from Dzidzienyo et al. (2018) and parameterized in D.3

Initial Parameters for Pyrolysis Model.

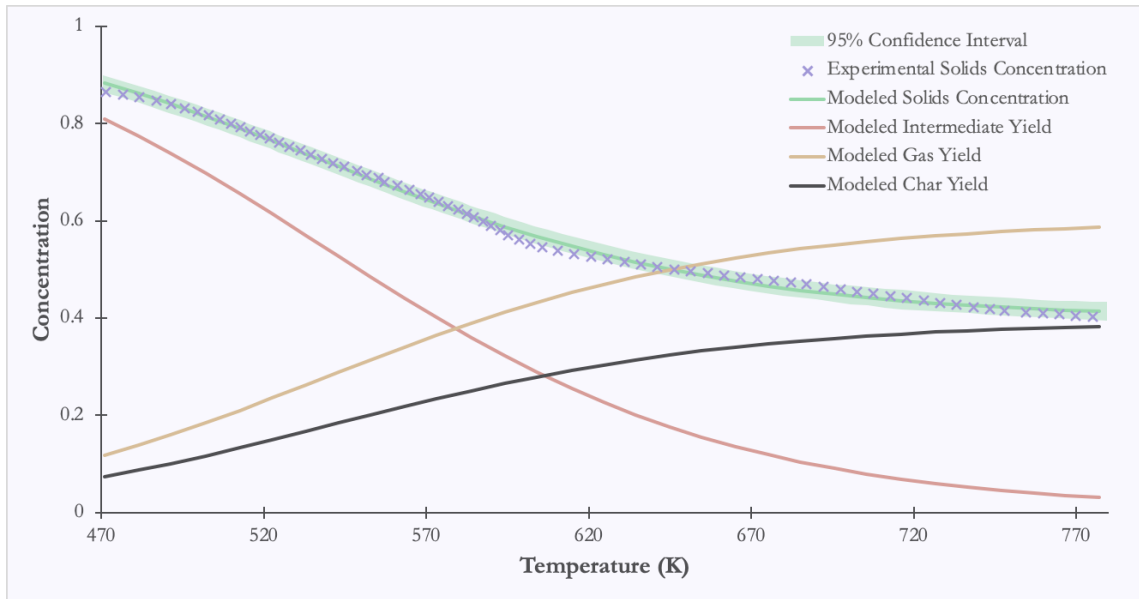


Figure 50. Pyrolysis model of *Salicornia* under a constant heating rate of 5 K min^{-1} and starting temperature of 298 K .

The range of temperatures displayed indicate the active pyrolysis regions for *Salicornia* biomass, excluding the dehydration ($273\text{-}470 \text{ K}$) and passive pyrolysis ($770\text{-}1075 \text{ K}$) stages. The modeled solids loss is represented in green with a 95% confidence interval in light green and the experimental data from Dzidzienyo et al. (2018) is in purple. The fit of the experimental data to the model proposed by Koufopoulos et al. (1989) proved to be a good fit with an R^2 value of 0.9998. As one may observe, nearly 30% of the conversion to char occurs earlier in the pyrolysis process in the temperature ranges of $470\text{-}615 \text{ K}$. This char yield is validated by falling within the range specified by other biomass pyrolysis studies of 25-40% depending on input biomass, heating rates, temperature, and residence times. (Balat, Balat, Kirtay, & Balat, 2009; Basu, 2013) Using the 30% conversion of biomass weight to char, the pyrolysis process would generate around 800 metric tons of char per year, offsetting the yearly coal consumption by 0.076%. This offset

percentage assumes a steel production amount of 5 million metric tons of crude steel per year and year-round operation.

6.5.3 *Effect on Overall Material Structure by Employing the Wetland System*

Step 4 of General ENA Modeling Methodology (ENAMM) from Figure 19 – Best Case Material/Water and Energy Structural Meta-Model

In Figure 43 of Section 6.2, we presented the original steel material, water, and energy network. We then applied ENAMM from CHAPTER 5 in the ENA of this steel industry meta-model. The results showed an opportunity for improvement by increasing the ecological metric LD. By examining the water, material, and energy flows through the network, we found that water accounted for the highest magnitudes of flows in the network. Therefore, we investigated the use of “decomposing” interventions to address the enormous water demand in the steel industry. We found that by incorporating contaminant-targeted constructed wetlands, and combining this process with pyrolysis, we could use less water and energy while producing energy-dense biochar in comparison to the original steel industry network. These structural changes from the original model are shown below in Figure 51.

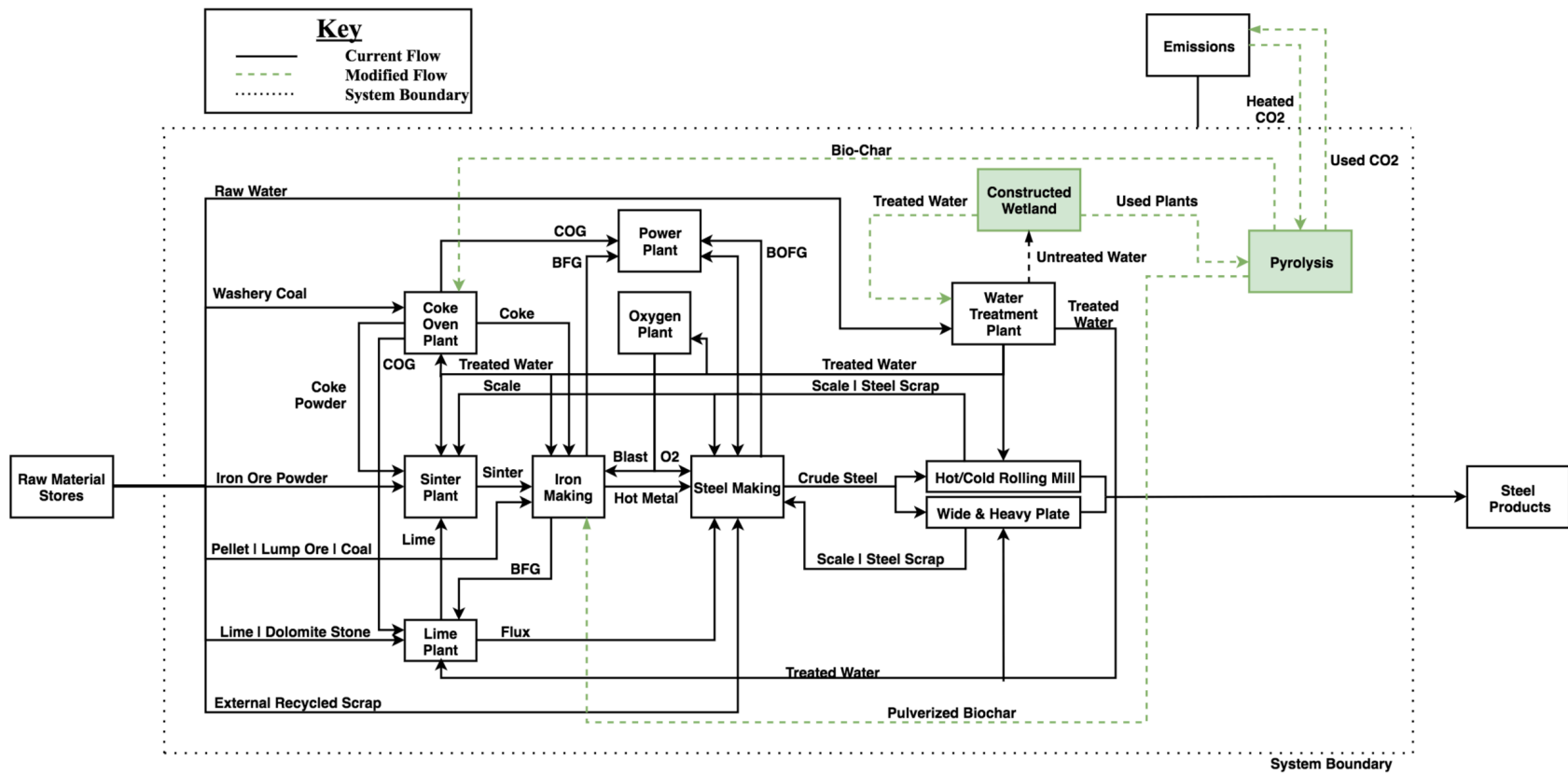


Figure 51. Steel Industry Material and Water Flow-Based Model with Constructed Wetlands and Pyrolysis Process

The diverging structural changes are shown in green in Figure 51. The flows in this altered model are shown below in Table 26.

Table 26. Material and Water Flows of a Steel Industry with Constructed Wetlands and Pyrolysis

Flow From	Flow To	Amount	Units
Washery Coal	Coking Plant	0.6173	ton/ton-cs
Water	Cold Rolling Plant	0.0996	ton/ton-cs
Power Grid	Entire	0.182	tce/ton-cs
Water	Entire	3.708	ton/ton-cs
Flue Emissions (Iron Plant)	Environment	0.0003	ton/ton-cs
Other Emissions (Steel Plant)	Environment	0.644	ton/ton-cs
Other Emissions (Coking Plant)	Environment	0.2207	ton/ton-cs
Dust Emissions (Coking Plant)	Environment	0.0009	ton/ton-cs
SO2 Emissions (Sinter Plant)	Environment	0.0012	ton/ton-cs
NOx Emissions (Coking Plant)	Environment	0.0016	ton/ton-cs
Effluent	Environment	0.13	ton/ton-cs
Con. Cast Slab (Steel Plant)	Hot Rolling Plant	0.56	ton/ton-cs
Water	Hot Rolling Plant	0.7148	ton/ton-cs
Pellet (Imported)	Iron Plant	0.3904	ton/ton-cs
Lump Ore (Imported)	Iron Plant	0.0981	ton/ton-cs
Coal (Imported)	Iron Plant	0.1977	ton/ton-cs
Sinter Ore	Iron Plant	1.2365	ton/ton-cs
Coke	Iron Plant	0.3173	ton/ton-cs
Oxygen Blast	Iron Plant	0.0012	tce/ton-cs
Water	Iron Plant	0.299	ton/ton-cs
Lime & Dolomite Stone (Imported)	Lime Plant	0.2942	ton/ton-cs
BFG	Lime Plant	0.0067	tce/ton-cs
COG	Lime Plant	0.0076	tce/ton-cs
Coke and Other Byproducts	Market	0.0346	ton/ton-cs
Wide & Heavy Plate Products	Market	0.229	ton/ton-cs
Cold Rolling Products	Market	0.0603	ton/ton-cs
Hot Rolled Plate Products	Market	0.4267	ton/ton-cs
COG	Outside Park Power Plant	0.0036	tce/ton-cs
BFG	Power Plant	0.0477	tce/ton-cs

Table 26. (Continued)

BOFG	Power Plant	0.0289	tce/ton-cs
COG	Power Plant	0.0013	tce/ton-cs
Water	Power Plant	0.7866	ton/ton-cs
Cold Rolling Scrap/Scale	Sinter Plant	0.015	ton/ton-cs
Cold Rolling Scrap/Scale	Steel Plant	0.0023	ton/ton-cs
Hot Rolling Scrap/Scale	Steel Plant	0.0731	ton/ton-cs
Wide & Heavy Plate Scrap/Scale	Sinter Plant	0.041	ton/ton-cs
Wide & Heavy Plate Scrap/Scale	Steel Plant	0.0058	ton/ton-cs
Lime Plant	Sinter Plant	0.0635	ton/ton-cs
Iron Ore Powder	Sinter Plant	0.9346	ton/ton-cs
Lime (Raw Material Yard)	Sinter Plant	0.0346	ton/ton-cs
Anthracite (Raw Material Yard)	Sinter Plant	0.0025	ton/ton-cs
Coke Powder	Sinter Plant	0.0538	ton/ton-cs
Water	Sinter Plant	0.0927	ton/ton-cs
Lime & Dolomite	Steel Plant	0.0808	ton/ton-cs
Oxygen	Steel Plant	0.026	tce/ton-cs
Hot Liquid Iron	Steel Plant	1.0096	ton/ton-cs
Water	Steel Plant	0.7475	ton/ton-cs
Other Emissions(Iron Plant)	Environment	1.5534	ton/ton-cs
Crude Steel	To Plate, HR, and CR	1	ton/ton-cs
Effluent	Water Treatment Plant	3.1162	ton/ton-cs
Con. Cast Slab (Steel Plant)	Wide & Heavy Plate Plant	0.25	ton/ton-cs
Wetlands	Entire	0.578	ton/ton-cs
Pyrolysis	Iron Plant	0.0675	ton/ton-cs
Treated Wetlands Water	Power Plant	0.3189	ton/ton-cs
Treated Wetlands Water	Steel Plant	0.1846	ton/ton-cs
Treated Wetlands Water	Water Treatment Plant	0.0151	ton/ton-cs
Treated Wetlands Water	Environment	0.2832	ton/ton-cs
Treated Wetlands Water	Cold Rolling Plant	0.0404	ton/ton-cs
Treated Wetlands Water	Hot Rolling Plant	0.0031	ton/ton-cs
Treated Wetlands Water	Iron Plant	0.0159	ton/ton-cs
Power Plant Water	Wetlands	0.374	ton/ton-cs
Wetlands Plants	Pyrolysis	0.091	ton/ton-cs

Table 26. (Continued)

Hot Rolling Plant Waste	Environment	0.085	ton/ton-cs
Oxygen Plant Waste	Environment	0.008	ton/ton-cs
Clean Waster	Environment	3.391	ton/ton-cs
Pyrolysis	Coking Plant	0.0235	ton/ton-cs
Coal (Imported)	Power Plant	0.95811	tce/ton-cs

Step 7 of General ENA Modeling Methodology (ENAMM) from Figure 19 – Calculation of Flow Network Metrics for Scenarios

The results from incorporating the structural and flow-based changes when applying ENA are shown below in Table 27.

Table 27. ENA Model Results of Original Steel Material and Flow Meta-Model with Results from the Model with Constructed Wetlands and Pyrolysis

Model Variation	Linkage Density (LD)	Connectance (C)	Finn Cycling Index (FCI)	Average Mutual Information (AMI)	Extent of Development (AC)
Water Network Model	2.7692	0.21302	0.1072	1.2397	0.28445
Water Network Model with Wetlands and Pyrolysis	3.6154	0.27811	0.1557	1.3977	0.29578

These results suggest the inclusion of the wetlands and pyrolysis processes were enough to meet and exceed the ENAMM recommended LD value of 3.54 from CHAPTER 5. However, the feasibility of these suggestions must be analyzed to fully understand the implications of their inclusion in the steel industrial network.

6.5.4 Cost Analysis of Employing the Wetland System

Step 8 of General ENA Modeling Methodology (ENAMM) from Figure 19 – Feasibility Analysis

The following sections explore some of the economic impacts of the suggested design interventions in this study. These include the capital costs, operations and maintenance costs, and the payback period or return on investment calculation.

6.5.4.1 Capital Cost Estimation of Constructed Wetlands

According to Kadlec (2009) a Free Water Surface Constructed Wetland (FWS) capital cost can be approximated by the equation:

$$\text{FSWC} = 194A^{0.69}$$

with an R^2 value of 0.79

Where Cost is in Thousands of US Dollars for the year 2006

Area (A) in hectares $0.03 \text{ ha } (300\text{m}^2) < A < 10,000 \text{ ha } (100,000,000 \text{ m}^2)$

In this study, our designed constructed wetland is a Horizontal Subsurface Flow (HSSF) Constructed Wetland. According to the same study, a FWS system is on average 0.31 ± 0.14 times less than the cost of an HSSF system. Combining these equations, the final equation to calculate the capital cost of the designed wetland in this study would take the form:

$$\text{HSSFC} = \frac{194A^{0.69}}{0.31 \pm 0.14}$$

Where $A = 74.626 \text{ ha}$ ($746,260\text{m}^2$) and Cost is in Thousands of US Dollars for the year
2006

Taking into account a cumulative rate of inflation of 28% from 2006 to the year 2020, the equation yields a capital cost price range of \$10,819,474.06 to \$28,639,754.14 in the year 2020.

6.5.4.2 Operations and Maintenance Cost estimation of Constructed Wetlands

Energy costs associated with gravity driven constructed wetlands are close to zero. Most of the O&M is associated with permit-related sampling and correspondence, followed by management of pumps, septic tanks, control panels, and other conventional treatment components. However, HSSF constructed wetlands are susceptible to eventual clogging at the inlets, and maintenance every 5 years for the assumed 15-year lifespan of the wetland can be assumed to be 15% of the construction cost, or \$1,622,921 to \$4,295,963. Spread over the lifespan of the project, these operations and maintenance costs range from $108,194.73\$ \text{ yr}^{-1}$ to $286,397.54\$ \text{ yr}^{-1}$.

6.5.4.3 Capital and Operating Costs of Biomass Pyrolysis

The capital costs associated with biomass pyrolysis vary greatly between applications.(Snyder, 2019) These are due to the biomass feedstocks, the method of pyrolysis (gasification, slow, fast), and other factors such as transport costs. The amount of dry biomass generated per day in this study is 4700 kg day^{-1} . Jin et al. (2017) showed a capital cost investment of 2 million Euro for a dry biomass feed rate of 0.25 metric tons per hour, similar to the feedstock rate of 0.19 metric tons per hour used in this study.

Using the conversion rate of 1.54 Euro to 1 US Dollar in May 2008, the 2 million Euro capital investment equals a 1.3 million US dollar investment in 2008. Assuming a cumulative rate of inflation of 19.9%, this would equal a \$1,558,498.95 capital investment. However, this value may be higher than the actual cost of implementation due to the higher feedstock rate in the cited literature.

The cost of anthracite in China is 1043.49 RMB per metric ton, or 147.28 US dollars per metric ton in the year 2020.(Xiaojiao Zheng et al., 2020) Therefore, the cost savings of using 800 metric tons of biochar per year in place of anthracite would result in a savings of 117,824 US dollars per year.

6.5.4.4 Estimated Payback Period of Suggested Design

Using the freshwater decrease of 6129 m³ hr⁻¹ to 3034 m³ hr⁻¹ found in this analysis and an assumed freshwater cost of 0.28\$/m³ and year-round operation, the total payback period from the freshwater savings can be calculated as below:

1 Year Operation (Business as Usual):

$$6129 \text{ m}^3 \text{ hr}^{-1} \times 24 \text{ hrs. day}^{-1} \times 365\text{-day yr}^{-1} \times 0.28\$ \text{ m}^{-3} = 15,033,211 \$ \text{ yr}^{-1}$$

1 Year Operation (With Wetlands):

$$3034 \text{ m}^3 \text{ hr}^{-1} \times 24 \text{ hrs. day}^{-1} \times 365\text{-day yr}^{-1} \times 0.28\$ \text{ m}^{-3} = 7,441,795 \$ \text{ yr}^{-1}$$

This leads to a savings of 7,591,416 \$ yr⁻¹. Therefore, the total initial investment of capital cost and O&M spread for the first year is:

Low End Estimate:

$$\begin{aligned} & (\text{Initial Investment Wetlands} + \text{Initial Investment Pyrolysis} + \text{O\&M - 1 year}) / (\text{Annual} \\ & \quad \text{Cash Flow from CW Savings} + \text{Pyrolysis Savings}) = \\ & (10,819,474.06\$ + 1,558,498.95\$ + 108,194.73\$) / (7,441,795 \$ \text{ yr}^{-1} + 117,824 \$ \text{ yr}^{-1}) = \\ & \quad 1.65 \text{ years} \end{aligned}$$

High End Estimate:

$$\begin{aligned} & (\text{Initial Investment} + \text{Wetlands} + \text{Initial Investment Pyrolysis} + \text{O\&M - 1 year}) / (\text{Annual} \\ & \quad \text{Cash Flow from CW Savings} + \text{Pyrolysis Savings}) = \\ & (28,639,754.14\$ + 1,558,498.95\$ + 286,397.54\$) / (7,441,795 \$ \text{ yr}^{-1} + 117,824 \$ \text{ yr}^{-1}) = \\ & \quad 4.03 \text{ years} \end{aligned}$$

Cost savings from the combined wetland and pyrolysis system originate from reduced freshwater treatment costs with slight additional savings from the use of biochar in place of coal for steel manufacturing. The use of constructed wetlands results in a 50% reduction of freshwater treatment, with an approximate savings of \$8,000,000 US dollars. Assuming the 24 MJ kg⁻¹ higher heating value from Waqas et al. (2018) for biochar, the 800 metric tons a year has an approximate energy savings of 19.2 TJ year⁻¹ or 3771 metric tons CO₂ equivalent, enough to power 638 homes in the United States for one year.(U.S.

Energy Information Administration, 2019a, 2019b; U.S. Environmental Protection Agency, 2020)

At a savings of 117,824 US dollars per year, the cost offset by the generation of biochar as a replacement for anthracite in the steel making process is limited when compared to the other costs of our proposed design. However, the incorporation of this pyrolysis process reduces the CSIs reliance on exterior material supply networks. This leads to an increased operational resiliency through self-sufficiency, a core component in the design of resilient and sustainable systems.(Fiksel, 2003) Savings from decrease water treatment and biochar utilization is balanced with increased costs from the capital and maintenance costs of the land and infrastructure of the constructed wetlands and pyrolysis facilities. Depending on cost assumptions, this cost analysis finds a 1.65 to 4.03-year payback period on the proposed biologically augmented system.

6.6 In Closing: Water, Energy, and Cost Savings with Biological Augmentation: A Possible Sustainable Framework

Sustainable industrial production under the challenges of climate change and growth requires more cyclic production processes that use materials and energy more efficiently. This chapter uses the ENAMM introduced from CHAPTER 5 to augment a water treatment system model in the steel industry with a coupled constructed wetland and pyrolysis process from the database introduced in CHAPTER 4. The contaminant-targeted wetlands treat a combined stream of cooling water and desalination concentrate while a pyrolysis process upcycles mature plants back into the steel manufacturing process as biochar, increasing both ENA metrics LD and FCI. We find that the plant *Salicornia*

europaea has the highest potential for chloride remediation in our steel wastewater application with a $3 \text{ g d}^{-1}\text{m}^{-2}$ uptake rate despite having the slowest growth rate of the studied plants. Our design approach results in an annual 50% decrease in total freshwater consumption and 800-metric ton biochar yield. Our feasibility analysis shows an investment payback period of the proposed design to be 1.65 to 4.03 years. The results from this study show the validity of the ENAMM with demonstratable sustainability achievements as compared to traditional engineering design approaches.

As shown, this study demonstrates how readily available technology can address these sustainability challenges within the steel industry by looking to nature to provide both services and insight into the organization of these systems. In this study the utilization of the syn-gas and bio-oil byproducts from the pyrolysis process is neglected, but its use could decrease the amount of coal required by a slightly modified on-site powerplant, further decreasing the implementation costs proposed in this work. Alternatively, the managed decisions that may vary upon implementation, such as the introduction of redundant systems to maintain robust operations, may increase this determined payback period. Finally, there are many other contaminants in ROC and cooling water in addition to Cl^- that may require a targeted batch-treatment constructed wetland or special environmental requirements such as lining equipment to protect groundwater resources. This consideration may require alteration of the presented design with a modified approach, which may further impact the economic and environmental findings of this study.

Although the current work shows a technologically feasible approach with a potential for cost, energy, and water savings in the CSI, the holistic sustainability claims in this study depend on intelligent implementation, as the alternative could result in

unintended consequences. The proposed structural changes for the CSI could introduce problems such as economic rebounding that would ultimately reduce the sustainability impacts found in this study. In addition, subsequent studies such as a Life Cycle Analysis are required to inform careful materials selection for the CW and pyrolysis facilities building and maintenance; inappropriate material choices could have unintended and ultimately destructive downstream impacts. Further analyses should move from these modeled results to experimental and pilot scale operations while taking into account these important considerations.

CHAPTER 7. SUMMARY AND FUTURE WORK

7.1 Summary

The current industrial production model meets population-driven demand in an unsustainable manner, generating vast amounts of environmental pollution and material waste that threatens global economic stability and changes Earth's climate. It is understood that a key element to developing a more sustainable manufacturing model is through efficient and effective resource utilization, a goal that mature biological systems achieve through the implementation of intricate decomposing networks. These decomposing networks are essential for a healthy and mature ecosystem because these organisms cycle nutrients and energy that would otherwise be lost and reintroduce them to different trophic levels in the ecosystem.

The fundamental qualities of increased connectivity and cycling behavior can be quantified in ecosystems through the use of Ecological Network Analysis (ENA). We used ENA and multivariate statistics to analyze over 100 ecosystems and found that of the twenty-four original ENA metrics, two metrics - one structural (Linkage Density [LD]) and one flow-based (Finn Cycling Index [FCI]) - were fundamental in explaining the greatest degrees of variance in a combined principle component analysis and cluster analysis. This suggests that the metrics values for LD and FCI that have been set by natural ecosystems may be key indicators of a healthy "balance" in network structure and the flows.

Accordingly, they may in turn be a guiding light in its application to sustainable engineered systems design.

In order to apply this finding, we then introduce a database of classified and categorized engineered “decomposers” as interventions to waste streams that would increase the ecological metrics LD and FCI when applied in the industrial realm. We then show how to model, quantify, and improve the performance of engineered systems with a generalized mathematical model to describe engineered systems components and a quantitative methodological approach called ENAMM that includes rules, goals, and suggestions, to ENA’s application to engineered systems. The ENAMM is then tested and validated through its application to two case studies.

The first case study is the structural analysis of an automobile manufacturing facility. This case study investigates the essential initial steps of the proposed ENAMM – the underlying assumptions one might propose, the identification and establishment of system boundaries, and the identification of the correct level of coarseness when breaking the high-level systems down to the components inside system boundaries. This case study also investigates scenario exploration to investigate how structural changes might bring system components together and form a more strongly connected component. Finally, this study shows the formation of a meta-model, by combining water, material, and energy components of an engineered system and calculating the progression of ENA values from the initial structure model to the final model.

The second case study explores the latter stages of the proposed ENAMM with an example of a carpet manufacturing recycling network. This study’s objective is to

demonstrate the flow and feasibility analysis of an engineered system using ENA. The feasibility analysis included the optimization of the economic ramifications of the assignment of flows in the network, the consideration of environmental costs through pollution generation, and achieving set target goals for the ENA metrics LD and FCI in the final model.

These carpet manufacturing and automobile manufacturing case studies highlight the fundamental differences of structural and material flow-based configurations in engineered systems as compared to those found in natural systems. Prior to scenario exploration using biological, technological, or hybrid interventions to target waste streams, these engineered systems demonstrate a focus on an efficient linear structure. We know from our analysis of 100 ecosystems that natural systems alternatively focus on optimizing the use of natural resources to live within the material constraints of their surroundings as demonstrated by higher values of Linkage Density and Finn Cycling Index. We found that by targeting those metric values achieved by natural systems, iteration of the structural and material-based configurations in engineered systems does in fact lead to improvements in material and energetic efficiency.

Finally, we present a final case study of steel manufacturing that includes all steps of the proposed ENAMM and demonstrates how readily available technology can address the sustainability challenges within the steel industry by looking to nature to provide both services and insight into the organization of these systems. This case study first develops a system-wide material and water model. Through a Mass Flow Analysis (MFA), the potential behind incorporating technological and biological interventions in the steel manufacturing water network is uncovered and thus the study shifts to exploring

interventions to waste in the water network. Using the ENAMM resulted in a sharp decrease of freshwater consumption and a slight decrease in coal consumption found in a large-integrated steel manufacturing park through the optimized bioaugmentation of constructed wetlands for water treatment and pyrolysis for energy generation. The results suggest a 1.65 to 4.03-year payback period and is a clear win for sustainability in the steel industry. This case study provided confirmation of the ENAMM applied to a top-to-bottom analysis of an engineered system, and the results demonstrate considerable improvement of costs in addition to the traditional sustainable benefits of increased material and energy efficiencies.

7.2 Contributions

The results uncovered in this dissertations journey contribute to both science and engineering in a meaningful way. The following sections describe these contributions.

7.2.1 Uncovering the Fundamental Differences in Structural and Flow-Based Configurations in Ecosystems as Compared to Engineered Systems

At the onset of this work, we sought to uncover the fundamental differences in the structural and flow-based configurations of ecosystems as compared to engineered systems. A limited understanding has shown that engineered systems were more linear in structural configuration than natural ecosystems but isolating the key measures from ENA that describe ecosystem functionality that could be applied to these engineered systems was not yet understood. Therefore, past attempts to model engineered systems from an ecological perspective using ENA have been less targeted and often include an array of

structural and flow-based measures. This undirected approach has unintended economic consequences when engineered systems are modeled in this manner.

Our research pushed closer to this understanding the ENA metrics that best represent the differences between engineered and natural ecosystems through an ENA-driven Principle Component Analysis and Cluster Analysis from multivariate statistics. The results showed the metrics LD and FCI to be the fundamental metrics to describing the variance of data in over 100 ecosystems. Armed with this knowledge, we then could develop waste-stream targeted “decomposers” from biological, technological, or hybrid interventions that would increase the metrics LD and FCI in engineered systems. We found through several case studies that designing engineering systems using these structural and flow-based metrics from ENA could close the material and energy efficiency performance gap found between these systems and ecosystems.

7.2.2 A Quantifiable and Adaptable Design Framework for Performing ENA Analysis in Engineered Systems

There is no such generalized modeling methodology for applying ENA to the iterative engineered systems today. As a result, much of the ENA of engineered systems is ad hoc and segmented to those academics that grasp the subjects of mathematics, engineering, and biology. A generalized modeling approach as presented in from CHAPTER 5 that shows an 8-step approach for the application of ENA to engineered systems with clearly defined rules, recommendations, and assumptions. This contribution provides more depth of where ENA could be applied and by whom. This also fortifies and

expands the underlying principles of closed loop cycling in the growing fields of Industrial Ecology and Circular Economy.

7.3 Limitations

Although the results from the steel industry case study show a technologically feasible approach with a potential for cost, energy, and water savings, the holistic sustainability claims depend ultimately on intelligent implementation, as the alternative could result in unintended consequences. The proposed structural changes for the steel manufacturing water network could introduce problems such as economic rebounding that would ultimately reduce the sustainability impacts found in this study. In addition, subsequent studies such as a Life Cycle Analysis are required to inform careful materials selection for the constructed wetlands and pyrolysis facilities building and maintenance; inappropriate material choices could have unintended and ultimately destructive downstream impacts.

Furthermore, it is imperative to remember that in this dissertation's proposed ENAMM, the overall analogy between ecosystems and engineered systems leaves much to be desired. Engineered systems are typically driven by profit alone, and thus we face the widespread environmental exploitation that exists today. Natural systems by contrast have evolved to live and survive through periods of food shortages and care nothing or even understand the concept of profit. As such, it is believed there will always be a struggle, or balance, between profit and environmental exploitation.

This work has clearly shown through several examples that an ecologically inspired metric-based approach to the conceptual design of engineered systems provides both

structural or flow-based translative insight to the configurations that lead to reduced natural resource consumption and material waste. However, this is demonstrated with a relatively small sample size of engineered and natural ecosystems in relation to the amount of these systems in the world. Inevitably, new data or unforeseen variations of systems configuration, quantification, and/or scaling will uncover the need to revisit the methodology proposed in this research.

7.4 Future Work

The work in this dissertation has set the stage for numerous potential research directions. Some of these directions include: the expansion of the proposed database of biological, technological, or hybrid solutions to engineered systems waste streams, the refinement and expansion of the ENAMM, and contributing to a design tool that allows non-experts from the design communities to design engineered systems using ENA without the use of computer programming. The following sections will explore each of these topics in more depth.

7.4.1 Database Expansion

The database presented in CHAPTER 4 is in its infancy. It has been designed from inception to be modular and is intended to grow with time. The intended focus of this dissertation's work on this database was a focus on biological or hybrid interventions. We targeted these systems for two reasons – (1) the majority of literature takes a technological approach to solving waste stream issues, therefore we thought it would be a greater scientific contribution to focus on areas that receive less attention and (2) It is the authors belief that natural or hybrid interventions that are either fully

or partially powered by renewable sources of energy (the sun) will be key in a future decarbonized economy.

Much more work needs to be done to uncover the vast potential that the biological, technological, or hybrid interventions can supply that we did not include in our database. Developing the parametric equations that allow for high level design estimates for treatment capacities and sizing is burdensome work. It requires hours of pouring over literature to find the studies that include the key pieces of information needed to estimate these treatment rates. Expanding this data will require a multi-disciplinary effort from areas of the sciences and engineering to address or may be possibly automated using tools in the growing field of machine learning. It is suggested that future researchers wanting to contribute, fork (create their own copy), merge, or manage this database should take into account a few considerations.

First, what is this intended use of this database? Are you developing your own tool for ENA modeling or something else? Do you just want to explore potential waste stream solutions? Answers to these questions will help you identify what this database can do for you. We provided this database in Excel format because it is recognizable by all, and we realize that everyone is not well versed in data management and manipulation. We originally explored the development of what is known as a relational database so that once the waste streams were categorized and classified, a user of our design tool would be given automatically generated interventions based on their engineered system model in a ENA design tool (see Section 7.4.3). A relational database management system such as MySQL, MS Server, or PostgreSQL could be used to effectively manage the data for this goal. However, we found that this approach may

be limiting and that users of such a design tool might want more flexibility for scenario exploration. This led to the question: what if users want to explore all potential options? Therefore, we explored options away from SQL and other relational databases such as MongoDB. Eventually it was concluded that future owners of this database shouldn't be limited and thus the unformatted database is provided in this dissertation.

Another question is if you expect to work on this database with others or alone. Some considerations could include data security and validation of user inputs for crowdsourced development efforts. As mentioned, hours of research are needed for just one of the interventions listed in this database. Unit transformations and calculations are often needed to develop the parametric equation. To ensure your database is accurate and based on reality, consider validation steps for contributors to your database so that one can manage access to those that are qualified or trusted. Models are only as good as the data and assumptions that lead to their development.

Finally, the scope on the current presentation of this database is surely limited based on the experience of the author. It is the hope that this database will grow, and morph based on input from subject matter experts across the sciences and engineering. It is the belief of the author that for the research in this dissertation to be utilized to its true potential, the more diversity of contributions will surely lead to better and more useful results.

7.4.2 Refinement of Generalized ENA Modeling Methodology (ENAMM)

The ENAMM introduced in CHAPTER 5 is an ambitious attempt to lay the foundations for a standardized assessment of engineered systems using ENA. There

will inevitably be a need for clarification, expansion, or alteration of the suggested approach, however the general structure should remain. Any modeling methodology should always leave room for input on improvement.

To make this suggested approach stronger, the application to a more diverse set of engineered systems is needed. It is suggested that these systems originate from different locations in the world, from different industries, and have different scales of operations. Our case study in CHAPTER 6 showed the modeling of a Basic Oxygen Furnace manufacturing operation in the steel industry in China. This type of manufacturing in the world is rarely conducted in western countries. Therefore, if our case studies were limited to the United States, or European Countries, we would have limited the input to the suggested methodology. There most assuredly will be lessons learned by the continuous application of this methodology. These lessons should lead to revisiting the assumptions and rules developed in the methodology to see if any modifications are required.

7.4.3 ENA Tool

The ENAMM established in CHAPTER 5 has steps that are difficult to implement without prior knowledge of computer coding, mathematical modeling, linear algebra, statistics, biological systems, and engineered systems. For the average person in the design community, or even in academia, this is a difficult combination of skills to obtain. Previous research has shown that novices show distinct differences and struggle with design-by-analogy execution as compared to experts (Fu et al., 2014). As such, we have started the work to develop a generalized ENA design tool that applies our generalized ENAMM in

CHAPTER 5 and interacts with the database presented in CHAPTER 4, but with an interactive general user interface with a navigable design environment. The initial tool is shown below in Figure 52.

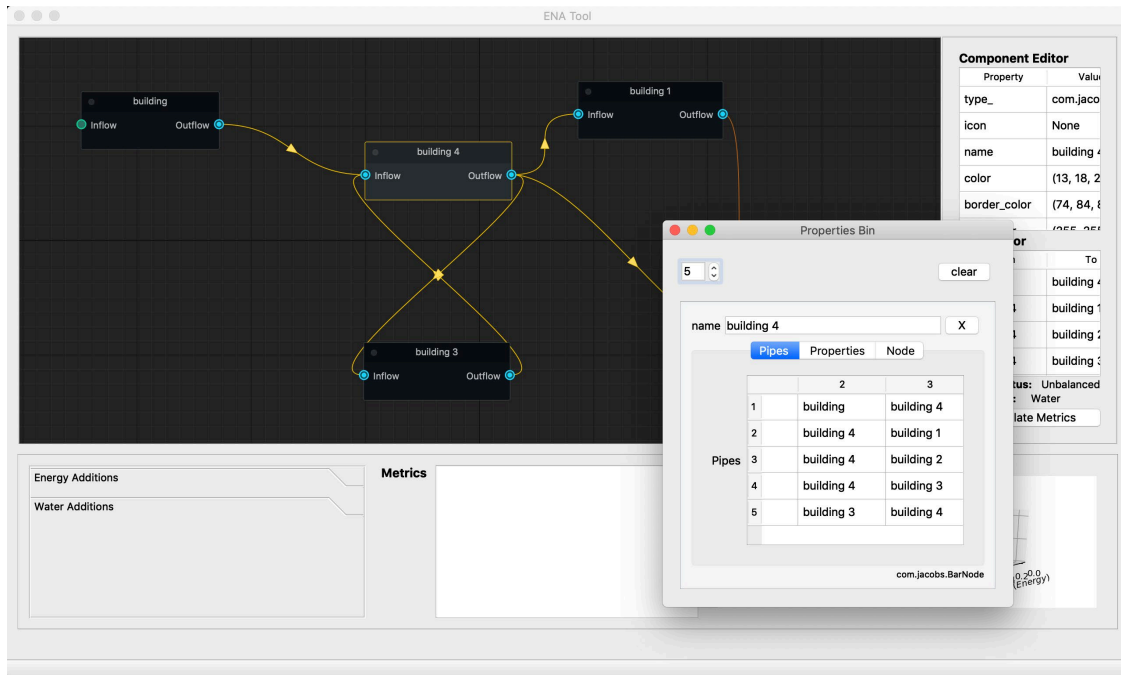


Figure 52. ENA Tool with Model Setup

The hope in this ENA tool's development is that it will help bridge the gap between a knowledgeable expert in ENA and members of the design community. The tool's intended use is not for an academic or ENA expert, but towards the architects, city planners, or engineers that know little of ENA but want to design more sustainable engineered systems.

This tool interface follows the general interface design principles found in literature (Lee, Eastman, Taunk, & Ho, 2010; Marcus, 1995; J. Nielsen). Some of these include visibility of system status, a clear match between the modeled system and the real world, user control and freedom, consistency and standards, flexibility and efficiency of use, aesthetic and minimalist design, and help and documentation.

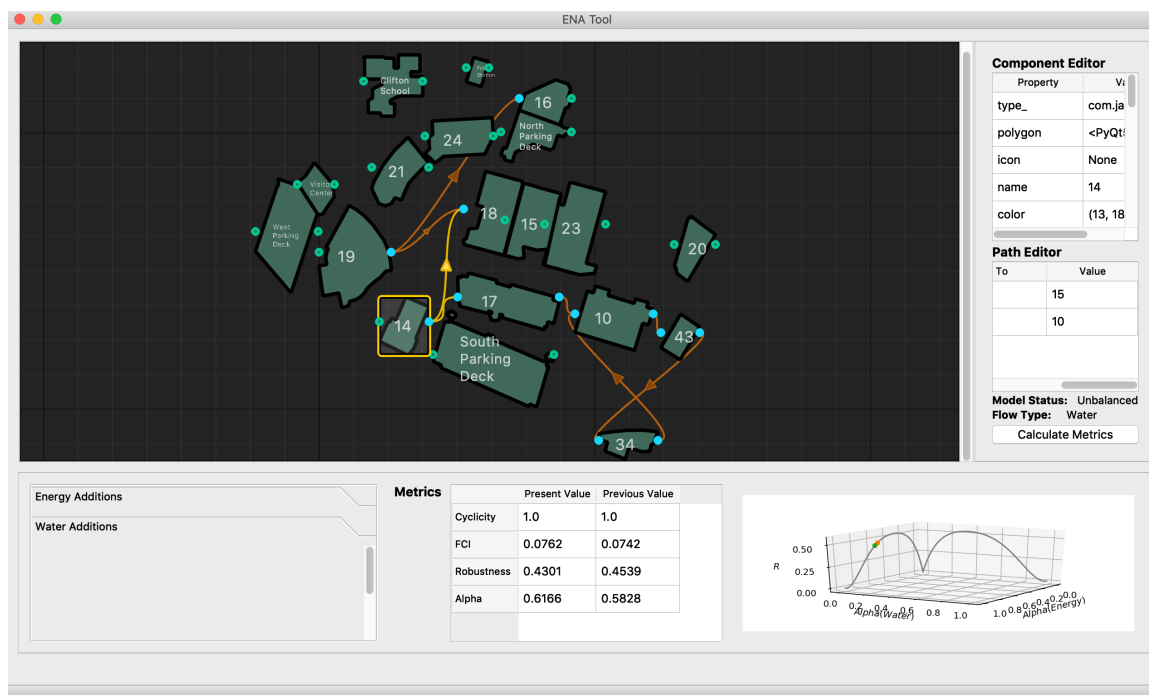


Figure 53. ENA Tool Showing Modeled System and Connections

Work still needs to be done to incorporate the database of biological, technological, and hybrid systems (bottom left of Figure 53, energy and water additions) presented in CHAPTER 4. In addition, full help documentation is needed to support a user. Finally, it is the hope of the author that future generations of this tool will integrate seamlessly with optimization solvers to maximize ENA metrics such as LD and FCI as shown in the feasibility step of Section 5.3.2 of this dissertation.

7.5 In Closing

Our world as we know it cannot function without vast amounts of industrial output. This industrial demand for output is only expected to increase with time. Looking to the past, one can clearly observe the track record of human-driven environmental degradation stemming from the onset industrial revolution. There is no debate that humans are to blame

for this environmental pillaging and the current climate crisis. Realizing this, we must immediately adapt our ways or face catastrophic consequences.

Adopting more holistic approach to the design of engineered systems, such as using natural ecosystems as a template for sustainable systems design, is one way to adapt. By providing a quantitative means and an established methodology for iteratively assessing engineered systems to achieve established design targets, it is believed that this dissertation provides a step towards changing the currently subjective (and often limited) practice of sustainable systems design. This approach would look to commonly regarded waste streams as potential resources and bring sustainability to the forefront of discussion in the design process, instead of an afterthought. These changes in approaching engineered systems design would be a big step towards that needed to face the current climate crisis and sustain the growing world population while still meeting industrial demand.

APPENDIX A. ECOSYSTEM EXTRACTION

This appendix highlights the methods used to extract ecosystems from the Ecopath with Ecosim software package and provides further background information on their origins. The first section of APPENDIX A. Ecosystem Extraction is the MATLAB code to extract the ecosystems. The second part is a complete list of the 100 ecosystems, their authors, and sources from literature.

A.1 MATLAB Subroutine

```
clc;
clear all;

%Statistics out Filename
out_fn = fullfile('ecopath_matlab-pkg',...
    'examples', sprintf('%s%s%s','results_',datetime('now'),'xlsx'));

%Desired Statistics Out
stat_d = {'n','Gen','Vul','TSTp','TSTf','Ltot','Lint','LD','C','Tavg','TSTfavg','Cavg',...
    'A','DC','O','AC','AMI','HR','DR','RU','Hmax','Hc','CE','Hsys','APL',...
    'TSTc','TSTs','FCI','FCIb','Qsum','Psum','catchTL','GE'};

%Calculate How many Ecosystems we have
numSystems = size(dir(fullfile('ecopath_matlab-pkg','examples', '*.EwEaccdb')),1);

%Gather the struct of names for our ecosystems
nameSystems = dir(fullfile('ecopath_matlab-pkg','examples', '*.EwEaccdb'));

%List of names
nameList = {nameSystems(:).name};

%Final Table of Stats for Export
s_Table = table('Size',[numSystems,numel(stat_d)],'VariableTypes',...
    {'double','double','double','double','double','double','double','double',...
    'double','double','double','double','double','double','double',...
    'double','double','double','double','double','double',...
    'double','double','double','double','double','double',...
    'double','double','double','double','double'},...
    'VariableNames',stat_d,'RowNames',nameList);
```

```

%Loop through ecosystems
for i = 1:numSystems
    %Update Console
    %Extract Name of System and Extension
    s_name_ext = strsplit(nameList{i},'.');
    fprintf("\n Currently Analyzing %s. %d of %d complete \n",s_name_ext(2012),i,numSystems);

    %Load access DB of Ecosystem

    %Error Handling
    try
        %Turn Warnings off
        w = warning('off');

        %Load Ecosystem
        Tb = mdb2ecopathmodel(fullfile('ecopath_matlab-pkg',...
            'examples', nameList{i}));

        %Turn Warnings back on
        warning(w);
        Tb2 = Tb.calcstanza;
        Tb3 = Tb.checkstanza;

        %isequaln(Tb.groupdata.b, Tb2.groupdata.b)
        %isequaln(Tb.groupdata.b, Tb3.groupdata.b)
        Ep = Tb.ecopath;
    %Write Metrics to File
    %     if any(Ep.EE > 1)
    %         warning('EE > 1, Model not balanced')
    %     end
    %     if any(Ep.GE > 1)
    %         warning('EE > 1, Model not balanced')
    %     end
    %Calculate Size of Matrix (Number of creatures + 3)
    m_size = size(Tb.networkindices.T,1);

    %Write Matrix to Excel File
    %Create sheet with ecosystem name
    %Strip out weird stuff if need be from the name
    s_name_out = regexp(s_name_ext(2012),'\(<[a-z]','${upper($1)}');
    s_name_out = regexp(s_name_out, '[\s-\."]', "");

    %Some names are too big for sheet names
    if strlength(s_name_out)>30
        s_name_out = s_name_out(1:30);
    end
    writematrix(Tb.networkindices.T,out_fn,'Sheet',s_name_out)

    %Convert Struct to Table
    tbl_stat_d = struct2table(getFields(Tb.networkindices,stat_d));

    %Update Final Stats Table
    s_Table(i,:) = tbl_stat_d;

```

```

        %Write Metrics to Excel File Under Matrix
        writetable(tbl_stat_d,...
            out_fn,'Sheet',s_name_out,'Range',...
            sprintf('%s%d','A',m_size +2));
    catch ME

        disp('error reading file, moving to next...')
        disp(ME.message)
        %rethrow(ME)
    end

end

%Write Final Stats to Excel File
writetable(s_Table,out_fn,'Sheet','AggregatedStats','WriteRowNames',true);

```

A.2 Ecosystems

Table 28. 100 Ecosystem Dataset

Name of the model	Author	Period	Location	Associated Publication
Albatross Bay	Okey, T.A.	1986-1993	Australia	Okey T.A.(2006). A trophodynamic ecosystem model of Albatross Bay, Gulf of Carpentaria: revealing a plausible fishing explanation for prawn catch declines CSIRO Marine and Atmospheric Research Paper
Aleutian Islands	Guénette, S.	1963-1963	United States of America	Guénette S.,Heymans S.J.J.,Christensen V.,Trites A.W.(2006). Ecosystem models show combined effects of fishing, predation, competition, and ocean productivity on Steller sea lions (<i>Eumetopias jubatus</i>) in Alaska Canadian Journal of Fisheries and Aquatic Sciences. pp 2495-2517
Alto Golfo de California	Morales-Zárate, M.V.	2004-2004	Mexico	Morales-Zárate M.V.,Arreguin-Sánchez F.,López-Martínez J.,Lluch-Cota S.E.(2004). Ecosystem trophic structure and energy flux in the Northern Gulf of California, México Ecological Modelling. pp 331-345
Azores	Morato, T.	1997-1998	Portugal	Morato, T., Lemey, E., Menezes, G., Pham, C. K., Brito, J., Soszynski, A., Pitcher, T. J., & Heymans, J. J. (2016). Food-Web and Ecosystem Structure of the Open-Ocean and Deep-Sea Environments of the Azores, NE Atlantic. <i>Frontiers in Marine Science</i> , 3. https://doi.org/10.3389/fmars.2016.00245
Baja California	Cisneros-Montemayor, A.M.	1970-1970	Mexico	Cisneros-Montemayor A.M.,Christensen V.,Arreguin-Sánchez F.,Sumaila R.U.(2012). Ecosystem models for management advice: An analysis of recreational and commercial fisheries policies in Baja California Sur, Mexico Ecological Modelling. pp 8-16
Black Sea	Gucu, A.	1990-1991	Not Affiliated	Gucu A.C.(2002). Can Overfishing be Responsible for the Successful Establishment of <i>Mnemiopsis leidyi</i> in the Black Sea? Estuarine, Coastal and Shelf Science. pp 439-451
Bolinao Coral Reef	Aliño, P.M.	1980-1981	Philippines	Aliño P.M.,McManus L.T.,McManus J.W.,Nañola Jr C.L.,Fortes M.D.,Trono Jr. G.C.,Jacinto G.S.,Aliño P.M.,McManus L.T.,McManus J.W.,Nañola Jr C.L.,Fortes M.D.,Trono Jr. G.C.,Jacinto G.S.(1993). Initial parameter estimations of a coral reef flat ecosystem in Bolinao, Pangasinan, Northwestern Philippines . pp 252-258.
British Columbia coast	Preikshot, D.B.	1950-2000	Canada	Preikshot D.B.(2007). The influence of geographic scale, climate and trophic dynamics upon North Pacific oceanic ecosystem models
Calvi Bay	Pinnegar, J.K.	1998-1999	France	Pinnegar J.K.,Polunin N.V.C.(2004). Predicting indirect effects of fishing in Mediterranean rocky littoral communities using a dynamic simulation model Ecological Modelling. pp 249-267
Campeche	Vega-Cendejas, M.E.	1985-1990	Mexico	Vega-Cendejas M.E.,Arreguin-Sánchez F.,Hernández M.(1993). Trophic fluxes on the Campeche Bank, Mexico . pp 206-213.
Grand Banks of Newfoundland	Bundy, A.	1985-1988	Canada	Bundy A.(2002). Adaptation of a Newfoundland-Labrador Ecopath model for 1985-1987 in statistical area 2J3KLNO to the area 2J3KL Information supporting past and present ecosystem models of Northern British Columbia and the Newfoundland shelf. pp 13-21. In Pitcher T.,Vasconcellos M.,Heymans S.J.J.,Brignall C.,Haggan N.
Cape Verde	Stobberup, K.A.	1981-1985	Cape Verde	Stobberup K.A.,Ramos V.D.M.,Coelho M.L.(2004). Ecopath model of the Cape Verde coastal ecosystem West African marine ecosystems: models and fisheries impacts. pp 39-56.

Table 28. (Continued)

Caribbean	Melgo, J.L.	1980-1981	Not Affiliated	Melgo J.L.,Morisette L.,Kaschner K.,Gerber L.(2009). Food web model and data for studying the interactions between marine mammals and fisheries in the Caribbean ecosystem Modelling the trophic role of marine mammals in tropical areas: data requirements, uncertainty, and validation. pp 53-120. In Morisette L.,Melgo J.L.,Kaschner K.,Gerber L.
Celestun mangrove	Vega-Cendejas, M.E.	1992-1994	Mexico	Vega-Cendejas M.E.,Arreguín-Sánchez F.(2001). Energy fluxes in a mangrove ecosystem from a coastal lagoon in Yucatan Peninsula, Mexico Ecological Modelling. pp 119-133
Central Atlantic	Vasconcellos, M.	1990-1991	Not Affiliated	Vasconcellos M.,Watson R.(2004). Mass-balance models of oceanic systems in the Atlantic West African marine ecosystems: models and fisheries impacts. pp 171-214. In Palomares M.L.D.,Pauly D.
Central Baltic Sea	Tomczak, M.T.	1974-1974	Not Affiliated	Tomczak M.T.,Niiranen S.,Hjerne O.,Blenckner T.(2012). Ecosystem flow dynamics in the Baltic Proper—Using a multi-trophic dataset as a basis for food–web modelling Ecological Modelling. pp 123-147
Central Chile 2005	Arancibia, H.	2005-2005	Chile	Arancibia H.,Neira S.(2008). Overview of the Chilean hake (<i>Merluccius gayi</i>) stock, a biomass forecast, and the jumbo squid (<i>Dosidicus gigas</i>) predator-prey relationship off central Chile (33°S-39°S) CalCOFI Reports. pp 104-115
Chesapeake present	Christensen, V.	2002-2002	United States of America	Christensen V.,Beattie A.,Buchanan C.,Hongguang M.,Martell S.J.D.,Latour R.J.,Preikshot D.,Sigrist M.B.,Uphoff J.H.,Walters C.J.,Wood R.J.,Townsend H.(2009). Fisheries Ecosystem Model of the Chesapeake Bay: Methodology, Parameterization, and Model Exploration NOAA Technical Memorandum
Contemporary Alosine	Dias, B.	2000-2001	United States	Dias, B. S., Frisk, M. G., & Jordaan, A. (2019). Opening the tap: Increased riverine connectivity strengthens marine food web pathways. PLOS ONE, 14(5), e0217008. https://doi.org/10.1371/journal.pone.0217008
Danajon Bank	Bacalso, R.T.M.	2010-2010	Philippines	Bacalso R.T.M.,Wolff M.(2014). Trophic flow structure of the Danajon ecosystem (Central Philippines) and impacts of illegal and destructive fishing practices Journal of Marine Systems 139: 103-118.
East Bass Strait	Cathy Bulman	1994-1994	Australia	Bulman C.,Condie S.,Furlani D.,Cahill M.,Klaer N.,Goldsworthy S.,Knuckey I.(2006). Trophic dynamics of the eastern shelf and slope of the south east fishery: impacts of and on the fishery Final Report for Fisheries Research & Development Corporation
Eastern Scotian Shelf	Bundy, A.	1995-2000	Canada	Bundy A.(2004). Mass balance models of the eastern Scotian Shelf before and after the cod collapse and other ecosystem changes Canadian Technical Report of Fisheries and Aquatic Sciences
Eastern Tropical Pacific	Olson, R.J.	1993-1997	Not affiliated	Olson R.J.,Watters G.M.(2003). A model of the pelagic ecosystem in the eastern tropical Pacific Ocean Inter-American Tropical Tuna Commission Bulletin. pp 135-248

Table 28. (Continued)

Eritrea	Tsehay, I.	1998-1998	Eritrea	Tsehay I., Nagelkerke L.A.J. (2008). Exploring optimal fishing scenarios for the multispecies artisanal fisheries of Eritrea using a trophic model Ecological Modelling. pp 319-333
Falkland Islands	Cheung, W.W.L.	1990-1991	Falkland Islands (Malvinas)	Cheung W.W.L., Pitcher T.J. (2005). A mass-balance model of the Falkland Islands fisheries and ecosystems Modeling Antarctic Marine Ecosystems. pp 65-84. In Palomares M.L.D., Pruvost P., Pitcher T.J., Pauly D.
Galapagos	Diego J. Ruiz	2006-2007	Ecuador	Ruiz, D. J., et al. (2016). "Elucidating fishing effects in a large-predator dominated system: The case of Darwin and Wolf Islands (Galápagos)." Journal of Sea Research 107: 1-11.
Georges Bank	Link, S.	1996-2000	United States of America	Link J.S., Griswold C.A., Methratta E.T., Gunnard J. (2006). Documentation for the Energy Modeling and Analysis eXercise (EMAX) Northeast Fisheries Science Center Reference Document
Schlei Fjord	Nauen, C.	1980-1981	Germany	Christensen V., Pauly D. (1992). The ECOPATH II - a software for balancing steady-state ecosystem models and calculating network characteristics Ecological Modelling. pp 169-185
Gironde estuary	Lobry, J.	1991-1998	France	Lobry J. (2004). Which reference pattern of functioning for estuarine ecosystems? The case of fish successions in the Gironde estuary
Golfo Dulce	Wolff, M.	1993-1995	Costa Rica	Wolff M., Hartmann H.J., Koch V. (1996). A pilot trophic model for Golfo Dulce, a fjord-like tropical embayment, Costa Rica Revista de Biología Tropical. pp 215-231
Grand Banks of Newfoundland	Heymans, S.J.J.	1990-1997	Canada	Heymans J.J. (2003). Ecosystem models of Newfoundland and Southeastern Labrador: Additional information and analyses for 'Back to the Future' Fisheries Centre Research Reports
Greenland West Coast	Pedersen, S.A.	1997-1998	Greenland	Pedersen S.A., Zeller D. (2001). A mass balance model for the West Greenland marine ecosystem Fisheries Impacts on North Atlantic Ecosystems: Models and Analyses. pp 111-127.
Guinea	Gascuel, D.	2004-2004	Guinea	Gascuel D., Guénette S., Diallo I., Sidibé A. (2009). Impact de la pêche sur l'écosystème marin de Guinée - Modélisation EwE 1985/2005 - Fisheries Centre Research Reports
Gulf of California	Lercari, D.	1990-2000	Mexico	Lercari D., Arreguín-Sánchez F. (2009). An ecosystem modelling approach to deriving viable harvest strategies for multispecies management of the Northern Gulf of California Aquatic Conservation: Marine and Freshwater Ecosystems. pp 384-397
Gulf of Carpentaria	Okey, T.A.	1990-1991	Australia	Okey T.A., Griffiths S., Pascoe S., Kenyon R., Miller M., Dell Q., Pillans R., Buckworth R.C., Gribble N., Engstrom N., Bishop J., Milton D., Salini J., Stevens J. (2007). The effect of illegal foreign fishing on the ecosystem in the Gulf of Carpentaria: management options and downstream effects on other fisheries Final Report to Australian Fisheries Management Authority Project 2006/825
Gulf of Maine	Link, S.	1996-2000	United States of America	Link J.S., Griswold C.A., Methratta E.T., Gunnard J. (2006). Documentation for the Energy Modeling and Analysis eXercise (EMAX) Northeast Fisheries Science Center Reference Document
Gulf of Mexico	Browder, J.A.	1980-1989	Mexico	Browder J.A., Browder J.A. (1993). A pilot model of the Gulf of Mexico continental shelf. pp 279-284. In Christensen V., Pauly D.

Table 28. (Continued)

Gulf of Nicoya	Wolff, M.	1993-1995	Costa Rica	Wolff M.,Chavarria J.B.,Koch V.,Vargas J.A.(1998). A trophic flow model of the Golfo de Nicoya, Costa Rica <i>Revista de Biología Tropical</i> . pp 63-79
Gulf of Salamanca	Duarte, L.O.	1997-1998	Colombia	Duarte L.O.,García C.B.(2004). Trophic role of small pelagic fishes in a tropical upwelling ecosystem <i>Ecological Modelling</i> . pp 323-338
Gulf of Thailande	Christensen, V.	1963-1964	Thailand	Christensen V.(1998). Fishery-induced changes in a marine ecosystem: insight from models of the Gulf of Thailand <i>Journal of Fish Biology</i> . pp 128-142
Humboldt Current	J.Tam, M. Taylor	1995-1996	Peru	Tam J.,Taylor M.H.,Blaskovic V.,Espinoza P.,Michael Ballón R.,Díaz E.,Wosnitza-Mendo C.,Argüelles J.,Purca S.,Ayón P.(2008). Trophic modeling of the Northern Humboldt current ecosystem, Part I: comparing trophic linkages under La Niña and El Niño conditions <i>Progress in Oceanography</i> . pp 352-365
Icelandic shelf	Mendy, A.	1997-1998	Iceland	Mendy, A. and E. Buchary (2001). Constructing an Icelandic Marine Ecosystem Model for 1997 Using a Mass-Balance Modelling Approach: 182-197.
Independence Bay	Taylor, M.H.	1996-1997	Peru	Taylor M.H.,Wolff M.,Mendo J.,Yamashiro C.(2008). Changes in trophic flow structure of Independence Bay (Peru) over an ENSO cycle <i>Progress in Oceanography</i> . pp 336-351
Irish Sea	Lees, K.	1973-1974	Ireland,U.K., and Northern Ireland	Lees K.,Mackinson S.(2007). An Ecopath model of the Irish Sea: ecosystems properties and sensitivity analysis. <i>Science Series Technical Report</i>
Jalisco and Colima Coast	Galván-Piña, V.H.	1995-1996	Mexico	Galván Piña V.H.(2005). Impacto de la pesca en la estructura, función y productividad del ecosistema de la Plataforma Continental de las costas de Jalisco y Colima, México
Jurien Bay	Lozano-Montes, H.M.	2007-2008	Australia	Lozano-Montes H.M.,Loneragan N.R.,Babcock R.C.,Jackson K.(2011). Using trophic flows and ecosystem structure to model the effects of fishing in the Jurien Bay Marine Park, temperate Western Australia <i>Marine and Freshwater Research</i> . pp 421-431
Kaloko Honokohau	Wabnitz, C.C.	2005-2005	United States of America	Wabnitz C.C.C.,Balazs G.,Beavers S.,Bjorndal K.A.,Bolten A.B.,Christensen V.,Hargrove S.,Pauly D.(2010). Ecosystem structure and processes at Kaloko Honokhau, focusing on the role of herbivores, including the green sea turtle <i>Chelonia mydas</i> , in reef resilience <i>Marine Ecology Progress Series</i> . pp 27-44
Kuosheng Bay	Lin, H.-J.	1998-2001	Taiwan	Lin H.-J.,Shao K.-T.,Hwang J.-S.,Lo W.-T.,Cheng I.-J.,Lee L.-H.(2004). A trophic model for Kuosheng Bay in northern Taiwan <i>Journal of Marine Science and Technology</i> . pp 424-432
Lesser Antilles	Mohammed, E.	2001-2005	Not Affiliated	Mohammed E.,Vasconcellos M.,Mackinson S.,Fanning P.,Heileman S.,Carocci F.(2008). Scientific Basis for Ecosystem-Based Management in the Lesser Antilles Including Interactions with Marine Mammals and Other Top Predators: A trophic model of the Lesser Antilles Pelagic Ecosystem FI:GCP/RLA/140/JPN Technical Document
Liberia	Kay, D.W.	2005-2006	Liberia	Kay D.W.(2011). Liberia report on Ecopath modeling Ecosystem-based fisheries management using Ecopath with Ecosim (EwE) software. pp 105-118. In Christensen V.,Villanueva C.
Mauritanie	Guenette, S.	1991-1991	Mauritania	Guenette S.,Meissa B.,Gascuel D.(2014). Assessing the Contribution of Marine Protected Areas to the Trophic Functioning of Ecosystems: A Model for the Banc d'Arguin and the Mauritanian Shelf <i>Plos One</i> . pp 1-16

Table 28. (Continued)

Mid-Atlantic Bight	Link, S.	1996-2000	United States of America	Link J.S., Griswold C.A., Methratta E.T., Gunnard J. (2006). Documentation for the Energy Modeling and Analysis eXercise (EMAX) Northeast Fisheries Science Center Reference Document
Moreton Bay Ecosystem	Esther Fondo	1990-2014	Australia	Fondo E.N., Chaloupka M., Heymans J.J., Skilleter G.A. (2015). Banning Fisheries Discards Abruptly Has a Negative Impact on the Population Dynamics of Charismatic Marine Megafauna
Morocco	Stanford, R.	1985-1987	Morocco	Stanford R., Lunn K., Guénette S. (2001). A preliminary ecosystem model for the Atlantic coast of Morocco for the mid-1980s Fisheries Impacts on North Atlantic Ecosystems: Models and Analyses. pp 314-344. In Guénette S., Christensen V., Pauly D.
Mount St Michel Bay	Le Pape Olivier	2003-2004	France	Arbach Leloup F., Desroy N., Le Mao P., Pauly D., Le Pape O. (2008). Interactions between a natural food web, shellfish farming and exotic species: the case of the Bay of Mont Saint Michel (France) Estuarine, Coastal and Shelf Science. pp 111-120
New Foundland	Ainsworth, C.H.	1985-1986	Canada	Ainsworth C.H., Sumaila R.U. (2005). Intergenerational valuation of fisheries resources can justify long-term conservation: a case study in Atlantic cod (<i>Gadus morhua</i>) Canadian Journal of Fisheries and Aquatic Sciences. pp 1104-1110
North Aegean	Tsagarakis K.	2003-2006	Greece, Turkey	Tsagarakis K., Coll M., Giannoulaki M., Somarakis S., Papaconstantinou C., Machias A. (2010). Food-web traits of the North Aegean Sea ecosystem (Eastern Mediterranean) and comparison with other Mediterranean ecosystems Estuarine, Coastal and Shelf Science. pp 233-248
North Atlantic	Vasconcellos, M.	1997-1998	Not Affiliated	Vasconcellos M., Watson R. (2004). Mass-balance models of oceanic systems in the Atlantic West African marine ecosystems: models and fisheries impacts. pp 171-214. In Palomares M.L.D., Pauly D.
North Benguela	Watermeyer, K.	1990-1991	Namibia	Watermeyer K.E., Shannon L.J., Roux J.P., Griffiths C.L. (2008). Changes in the trophic structure of the northern Benguela before and after the onset of industrial fishing African Journal of Marine Science. pp 383-403
North Sea	Christensen, V.	1981-1982	Not Affiliated	Christensen V. (1995). A Model of Trophic Interactions in the North Sea in 1981, the Year of the Stomach Dana. pp 1-28
North South of China Sea	Cheung, W.W.L.	1970-1971	China, Vietnam	Cheung W.L. (2007). Vulnerability of marine fishes to fishing: from global overview to the Northern South China Sea
Northern British Columbia	Ainsworth, C.H.	2000-2001	Canada	Ainsworth C., Heymans J.J., Pitcher T.J., Vasconcellos M. (2002). Ecosystem Models of Northern British Columbia for the Time Periods 2000, 1950, 1900 and 1750 Fisheries Centre Research Reports
Northern Gulf of Mexico	Sagarese, S.	2005-2009	United States	Sagarese, S. R., et al. (2017). "Progress towards a next-generation fisheries ecosystem model for the northern Gulf of Mexico." Ecological Modelling 345: 75-98.
Northern Gulf of St Lawrence	Savenkoff, C.	1990-1991	Canada	Savenkoff C., Bourdages H., Castonguay M., Morissette L., Chabot D., Hammill M.O. (2004). Input data and parameter estimates for ecosystem models of the northern Gulf of St. Lawrence (mid-1990s) Canadian Technical Report of Fisheries and Aquatic Sciences
Northern Humboldt Current	Tam, J.	1997-1998	Peru	Tam J., Taylor M.H., Blaskovic V., Espinoza P., Michael Ballón R., Díaz E., Wosnitza-Mendo C., Argüelles J., Purca S., Ayón P. (2008). Trophic modeling of the Northern Humboldt current ecosystem, Part I: comparing trophic linkages under La Niña and El Niño conditions Progress in Oceanography. pp 352-365

Table 28. (Continued)

Northwest Africa	Morissette, L.	1987-1987	Not Affiliated	Morissette L., Melgo J.L., Kaschner K., Gerber L., Bamy I.L. (2009). Food web model and data for studying the interactions between marine mammals and fisheries in the Northwest African ecosystem Modelling the trophic role of marine mammals in tropical areas: data requirements, uncertainty, and validation. pp 6-52.
Orbetello Lagoon	Brando, V.E.	1995-1995	Italy	Brando V.E., Ceccarelli R., Libralato S., Ravagnan G. (2004). Assessment of environmental management effects in a shallow water basin using mass-balance models Ecological Modelling. pp 213-232
Peru	Jarre-Teichmann, A.	1973-1979	Peru	Jarre-Teichmann A., Pauly D. (1993). Seasonal Changes in the Peruvian Upwelling Ecosystem. pp 307-314. In Christensen V., Pauly D.
Port Cros	Valls, A.	1998-2008	France	Valls A., Gascuel D., Guénette S., Francour P. (2012). Modeling trophic interactions to assess the effects of a marine protected area: case study in the NW Mediterranean Sea Marine Ecology Progress Series. pp 201-201
Port Phillip Bay	Fulton, E.A.	1994-1995	Australia	Fulton E.A., Smith T. (2002). Ecosim Case Study: Port Phillip Bay, Australia The Use of Ecosystem Models to Investigate Multispecies Management Strategies for Capture Fisheries. pp 83-93. In Pitcher T., Cochrane K.
Portofino	Prato, G.	2007-2014	Italy	Prato, G., C. Barrier, P. Francour, V. Cappanera, V. Markantonatou, P. Guidetti, L. Mangialajo, R. Cattaneo-Vietti, and D. Gascuel. 2016. Assessing interacting impacts of artisanal and recreational fisheries in a small Marine Protected Area (Portofino, NW Mediterranean Sea). Ecosphere 7(12):e01601.
Prince William Sound	Okey, T.A.	1994-1996	United States of America	Okey T.A., Wright B.A. (2004). Toward ecosystem-based extraction policies for Prince William Sound, Alaska: integrating conflicting objectives and rebuilding Pinnipeds Bulletin of Marine Science. pp 727-747
Raja Ampat	Ainsworth, C.H.	2005-2006	Indonesia	Pitcher T.J., Ainsworth C.H., Bailey M. (2007). Ecological and economic analyses of marine ecosystems in the bird's head seascape, Papua, Indonesia: I Fisheries Centre Research Reports
Restored Alosine Biomass	Dias, B.	2000-2001	United States	Dias, B. S., Frisk, M. G., & Jordaan, A. (2019). Opening the tap: Increased riverine connectivity strengthens marine food web pathways. PLOS ONE, 14(5), e0217008. https://doi.org/10.1371/journal.pone.0217008
Santa Pola Bay	Bayle-Sempere, J.T.	2001-2007	Spain	Bayle-Sempere J.T., Arreguín-Sánchez F., Sanchez-Jerez P., Salcido-Guevara L.A., Fernandez-Jover D., Zetina-Rejón M.J. (2013). Trophic structure and energy fluxes around a Mediterranean fish farm Ecological Modelling. pp 135-147
Sechura Bay	Taylor, M.H.	1996-1997	Peru	Taylor M.H., Wolff M., Vadas F., Yamashiro C. (2008). Trophic and environmental drivers of the Sechura Bay Ecosystem (Peru) over an ENSO cycle Helgoland Marine Research. pp 15-32
Sierra Leone	Heymans, S.J.J.	1990-1991	Sierra Leone	Heymans J.J., Vakily J.M. (2004). Structure and dynamics of the marine ecosystem off Sierra Leone for three time periods: 1964, 1978, 1990 West African marine ecosystems: models and fisheries impacts. pp 160-169. In Palomares M.L.D., Pauly D.
Sinaloa sur MEXICO	Salcido-Guavara, L.A.	1994-1997	Mexico	Salcido Guevara L.A. (2006). Estructura y flujos de biomasa en un ecosistema bentónico explotado en el Sur de Sinaloa, Mexico
Sirinhaém River	Lira, A.	2013-2015	Brazil	Lira, A., Angelini, R., Le Loc'h, F., Ménard, F., Lacerda, C., Frédou, T., & Lucena Frédou, F. (2018). Trophic flow structure of a neotropical estuary in northeastern Brazil and the comparison of ecosystem model indicators of estuaries. Journal of Marine

Table 28. (Continued)

Sonda de Campeche	Manickchand-Heileman, S.	1988-1994	Mexico	Manickchand-Heileman S.,Soto L.A.,Escobar E.(1998). A Preliminary Trophic Model of the Continental Shelf, South-western Gulf of Mexico Estuarine, Coastal and Shelf Science. pp 885-899
South Benguela	Shannon, L.	1978-1979	South Africa	Shannon L.J.,Moloney C.L.,Jarre A.,Field J.G.(2003). Trophic flows in the southern Benguela during the 1980s and 1990s Journal of Marine Systems. pp 83-116
South Shetlands	Bredesen, E.L.	1990-2000	Antarctica	Bredesen, E. L. (2003). Krill and the Antarctic : finding the balance (T). Retrieved from https://open.library.ubc.ca/collections/ubctheses/831/item/s/1.0074873
Southern Brazil	Vasconcellos, M.	1980-1981	Brazil	Vasconcellos M.,Gasalla M.A.(2001). Fisheries catches and the carrying capacity of marine ecosystems in southern Brazil Fisheries Research. pp 279-295
Southern Gulf St Lawrence	Savenkoff, C.	1994-1996	Southern Canada	Savenkoff C.,Bourdages H.,Swain D.P.,Despatie S.-P.,Hanson M.J.,Méthot R.,Morissette L.,Hammill M.O.(2004). Input data and parameter estimates for ecosystem models of the southern Gulf of St. Lawrence (mid-1980s and mid-1990s) Canadian Technical Report of Fisheries and Aquatic Sciences
Southern New England	Link, S.	1996-2000	United States of America	Link J.S.,Griswold C.A.,Methratta E.T.,Gunnard J.(2006). Documentation for the Energy Modeling and Analysis eXercise (EMAX) Northeast Fisheries Science Center Reference Document
Sri Lanka	Haputhantri, S.S.K.	2000-2001	Sri Lanka	Haputhantri S.S.K.,Villanueva M.C.S.,Moreau J.(2008). Trophic interactions in the coastal ecosystem of Sri Lanka: An ECOPATH preliminary approach Estuarine, Coastal and Shelf Science. pp 304-318
Sítios Novos reservoir	Bezerra, LAV	2011-2012	Brazil	Bezerra, L. A. V.; Angelini, R.; Vitule, Jean R. S.; Coll, Marta; Botero, J. I. S. Food web changes associated with drought and invasive species in a tropical semiarid reservoir. Hydrobiologia, v. 817, p. 475-489, 2018. https://doi.org/10.1007/s10750-017-3432-8
Sørfjord	Falk-Petersen, J.	1993-1996	Norway	Falk-Petersen J.(2004). Ecosystem effects of red king crab invasion - a modelling approach using Ecopath with Ecosim
Tampa Bay	Chagaris, David	2005-2010	United States	D. Chagaris & B. Mahmoudi, 2010. Assessing the influence of bottom-up and top-down processes in Tampa Bay using Ecopath with Ecosim. In: Cooper, S.T. (ed.). Proceedings, Tampa Bay Area Scientific Information Symposium, BASIS 5: 20-23 October 2009. St. Petersburg, FL. pp 263-274.
Terminos Lagoon	Manickchand-Heileman, S.	1980-1990	Mexico	Manickchand-Heileman S.,Arreguín-Sánchez F.,Lara-Domínguez A.,Soto L.A.(1998). Energy flow and network analysis of Terminos Lagoon, SW Gulf of Mexico Journal of Fish Biology. pp 179-197
Thau	Palomares, M.L.D.	1980-1989	France	Palomares M.L.D.,Reyes-Marchant P.,Lair N.,Zainure M.,Barnabé G.,Lasserre G.(1993). A Trophic Model of a Mediterranean Lagoon, Etang de Thau, France . pp 224-229.
Mid Atlantic Bight	Okey, T.A.	1995-1998	United States of America	Okey T.A.(2001). A 'straw-man' Ecopath model of the Middle Atlantic Bight continental shelf, United States Fisheries Impacts on North Atlantic Ecosystems: Models and Analyses. pp 151-166. In Guenette S.,Christensen V.,Pauly D.
South Atlantic Continental Shelf	Okey, T.A.	1995-1998	United States of America	Okey T.A.,Pugliese R.(2001). A preliminary Ecopath model of the Atlantic continental shelf adjacent to the Southeastern United States Fisheries Impacts on North Atlantic Ecosystems: Models and Analyses. pp 167-181. In Guenette S.,Christensen V.,Pauly D.,Guenette S.,Christensen V.,Pauly D.

Table 28. (Continued)

Venezuela shelf	Mendoza, J.J.	1980-1989	Venezuela	Mendoza J.J.(1993). A preliminary biomass budget for the Northeastern Venezuela shelf ecosystem . pp 285-297. In Christensen V.,Pauly D.
West Coast of Peninsular	Christensen, V.	1972-1973	Malaysia	Christensen V.,Garces L.,Silvestre G.,Pauly D.,Christensen V.,Garces L.,Silvestre G.,Pauly D.,Christensen V.,Garces L.,Silvestre G.,Pauly D.(2003). Fisheries Impact on the South China Sea Large Marine Ecosystem: A Preliminary Analysis using Spatially-Explicit Methodology . pp 51-62.
West coast of Sabah	Garces, L.R.	1972-1973	Malaysia	Garces L.R.,Man A.,Ahmad A.T.,Mohamad-Norizam M.,Silvestre G.T.(2003). A trophic model of the coastal fisheries ecosystem off the West Coast of Sabah and Sarawak, Malaysia . pp 333-352.
West Scotland	Morissette, L.	2000-2004	France, U.K., and Northern Ireland	Morissette L.,Pitcher T.(2005). Model structure and balancing Ecosystem Simulation Models of Scotland's West Coast and Sea Lochs. pp 5-24, 30-40-5-24, 30-40. In Haggan N.,Pitcher T.
Western Channel	Araújo, J.N.	1993-1994	France, U.K., and Northern Ireland	Araújo J.N.,Mackinson S.,Ellis J.R.,Hart P.J.B.(2005). An Ecopath model of the western English Channel ecosystem with an exploration of its dynamic properties Science Series Technical Report
Western Tropical Pacific Ocean	Godinot, O.	1990-2001	Not Affiliated	Godinot O.,Allain V.(2003). A preliminary Ecopath model of the warm pool pelagic ecosystem Standing Committee on Tuna and Billfish Working Paper
Yucatan	Arreguín-Sánchez, F.	1987-1988	Mexico	Arreguín-Sánchez F.,Seijo J.C.,Valero-Pacheco E.(1993). An application of ECOPATH II to the North Continental Shelf Ecosystem of Yucatan, Mexico . pp 269-278.

APPENDIX B. FULL DATABASE OF BIOLOGICAL TECHNOLOGICAL AND HYBRID SOLUTIONS

This appendix shows the source for the full database of biological, technological, or hybrid solutions to common waste streams. In the first section of this appendix is a snapshot of the full database that can be found at the following link: <https://drive.google.com/file/d/1He2X1Ts-1i4pVxRCPg5iE0Ra9-h9RWIE/view?usp=sharing> or by contacting Dr. Bert Bras at bert.bras@me.gatech.edu.

B.1 Database

Table 29. Database of Biological, Technological, and Hybrid Solutions

Waste Number	Method of Recovery	Treatment Rate	Rate Units	Fate	Limitations	Requires Further Post-Processing (Refinement)	Source
1	Green Roof	1.03	$\text{g m}^{-2} \text{ yr}^{-1}$	Deposition onto plants	112 \$ m ⁻² cost average for extensive install, but highly variable	FALSE	(Manso, Teotônio, Silva, & Cruz, 2021)
2	Green Roof	1.96	$\text{g m}^{-2} \text{ yr}^{-1}$	Deposition onto plants	112 \$ m ⁻² cost average for extensive install, but highly variable	FALSE	(Manso et al., 2021)
3	Zeolite Transformation Under Atmospheric Conditions	0.5	$\text{g g}^{-1} \text{ yr}^{-1}$	Zeolite Na-X (useful for soil/groundwater remediation of heavy metals such as Cd through adsorption)	Needs alkaline activator sodium hydroxide at rate of 1.5 mol/L NaOH	FALSE	(Zgureva, Boycheva, Behunová, & Václavíková, 2020)
4	Fermentation Using Microbial Strain (Recombinant E. coli)	0.33	$\text{g L}^{-1} \text{ h}^{-1}$	PHA - Bioplastic (biomedical, agricultural and industrial applications)	Needs Batch Bioreactor Infrastructure	FALSE	(Pais et al., 2014)
5	Fermentation Using Microbial Strains (Mixed mesophilic cultures)	4.8	$\text{L L}^{-1} \text{ d}^{-1}$	Hydrogen Gas		FALSE	(Ren et al., 2007)
6	Fermentation Using Microbial Strains (Mixed mesophilic cultures)	3	$\text{L L}^{-1} \text{ d}^{-1}$	Hydrogen Gas		FALSE	(Hussy, Hawkes, Dinsdale, & Hawkes, 2003)
7	Pyrolysis	.3-.43	$\text{g g}^{-1} \text{ hr}^{-1}$	Biochar	Horizontal tube furnace 300-950 deg C	FALSE	(Elkhalifa, Al-Ansari, Mackey, & McKay, 2019)
8	Pyrolysis	.35-.6	$\text{g g}^{-1} \text{ hr}^{-1}$	Biochar	Fixed bed horizontal tube 300-700 deg C	FALSE	(Elkhalifa et al., 2019)
9	Bioconversion via SHF with <i>Saccharomyces cerevisiae</i>	0.0057	$\text{mg ml}^{-1} \text{ hr}^{-1}$	Bioethanol (44.89% maximal ethanol yield)	Requires LHW near critical water pretreatment before bioconversion; max ethanol production is 200C, 2 ml min ⁻¹ flow, and 200 bar; Max ethanol productivity at 0.5g solid loading	FALSE	(Uyan, Alptekin, Cebi, & Celiktaş, 2020)
10	Codigestion	582.53	$\text{kg kg}^{-1} \text{ d}^{-1}$	Methane Gas	Produces (6.93 t biogas d ⁻¹) , (10.3 t digested sludge DM d ⁻¹), and (2.19 t methane d ⁻¹) from inputs of 7.15 t Sewage Sludge DM d ⁻¹ , 4.68 t Municipal Biowaste DM d ⁻¹ , 1.28 t Kitchen Waste DM d ⁻¹ inputs. Assumes densities of 1.2 kg m ⁻³ for biogas and .669 kg m ⁻³ for methane	FALSE	(Blank & Hoffmann, 2011)

APPENDIX C. CASE STUDIES SUPPLEMENTAL INFORMATION

This appendix introduces the supplemental information for the Carpet Manufacturing Recycling Network case study in CHAPTER 5. This appendix covers the model development and coding in MATLAB.

C.1 Model Script Development

This case study seeks to assign flow values to our carpet recycling modeling that meets customers' demands and decreases overall system costs while taking into account environmental and ecological metric considerations. Beginning with the inputs and outputs, a flow-based matrix is generated. Initial flow amounts to and from system components of the known system, or reasonable approximations for steady-state values, is directly inputted into the MATLAB Optimization Program into the Flow Matrix. The matrix must be square of size $(N+3) \times (N+3)$ where N represents the number of components in the system. Flows are defined as moving from row (i) to column (j) in the matrix. The component entry in row i and column j would be denoted as t_{ij} . Row 0 represents imports from outside the system. Rows 1 through N represent exchanges inside the system between actors. Columns $N+1$ and $N+2$ represent exports to outside the system. Column $N+1$ is usable exports, those that could be utilized with additional processing or linkages, and Column $N+2$ is unusable (all value is gone) Rows $N+1$ and $N+2$, as well as column 0, should be empty.

Next, the user must input the minimum flows each component needs in a Minimum Flow Matrix, which imposes constraints on flow values required to maintain system functioning and prevents the optimization from reducing these cells below required levels. The Import Cost Matrix enables users to account for the cost of importing materials into the system. This is a $N \times 1$ vector specifying the initial cost of a specific import per unit (e.g., \$/kg or \$/kWh). This will also enable us to iterate upon the environmental impact “cost” function, facilitating the incorporation of upstream and embedded emissions brought into the system in the form of material imports.

After the material costs, there is a Transformation Energy Matrix. This is a $N+3 \times N+3 \times 2$ matrix specifying the energy required to convert one material to another in the first dimension and the specific cost associated with such conversion on an individual level in the second dimension. If energy is obtained from the same source (e.g. a power plant with set \$/kWh then the cost would be the same across the dimensions.

In order to account for distance constraints on flows between actors and to calculate emissions due to transportation, our model contains a Distance Matrix. This should be a $N+3 \times N+3$ matrix specifying the distance limitations of a system component to downstream component. For example, if flow i to j has a distance limitation of 150 meters, the d_{ji} cell should read “150.”

C.2 Data Pre-Processing

The data in the carpet manufacturing recycling network was not initially in a form that was readily analyzable using the MATLAB script above. As a result, this data had to be put in the form to match the required inputs. This meant taking the constraint, cost, emission, and flow information from the Reap and Layton studies and converting it to the matrices that were needed for the MATLAB code. Looking at the previous studies, the networks created for the ecological network analysis did not include all of the actors within the system. This network included 29 actors: the 13 counties where the carpet was distributed, the 13 reuse facilities tied to those counties, the carpet manufacturer, and the 2 recycling actors for nylon and PVC recycling. It did not account for the 9 landfills that are present in the system and the exclusion of those actors changes the results of the ecological metrics. In our case study of this system, these landfill actors were included, as these are critical pieces of the network. Their inclusion is needed to fully calculate operational and emissions costs and maintain mass balances.

The new network has 38 actors; the original 29 of the previous study with the 9 landfill actors added. With these new actors, the value for the Finn Cycling Index will likely be lower because new actors are being added, but no new cycling is added due to the actors being landfills. That said, our main objective is to see if the trend still remains of maximizing the ecological metrics while minimizing cost and emissions, the exact values for those metrics are not of critical concern. To compare similar results to Layton and Reap, we began by running our optimization routine and were able to generate an “optimized” flow matrix. Using this matrix, we then removed the landfill actors and ran this matrix

through their traditional (Equations 9, 10, and 11 in Section 5.5) and bio-inspired (Equations 6, 7, and 8 in Section 5.5) objective functions based off our new flow values.

C.2 MATLAB Code

```
%%Authored by Stephen Malone
%%11/20/2017
%%Copyright 2017. Georgia Institute of Technology

function [EC] = EmissionsCost(x, distance,user_Emissions,user_TransportationEmissions, ga)

if ga == 1
    x = reshape(x,size(x6));
end
    EC = 0;
    emissionGoals = [6.67E9 3.17E7 3.02E5 3.06E7 2.25E7 1.43E3 1.75E7 3.5E4 52 4.35E6
3.02E6 1.5E7];
    weightF = 1/13;

    %Speed up process by only looping over only non-zero records
    [nonZ_r, nonZ_c] = find(x);

    %initialize emissions holder
    emH = zeros(1,numel(emissionGoals));

    %Find all non-zero elements in matrix and multiply the flow amount by
    %the distance for transportation and the emissions associated with
    %that tranporation. Add this to the total emissions
    if ~isempty(nonZ_r)

        for i = 1:length(nonZ_r)

            for k = 1:length(emissionGoals)
                %add emissions costs
                emH(k) = emH(k) + x(nonZ_r(i), nonZ_c(i))*user_Emissions(nonZ_r(i), nonZ_c(i),k);
                %add transportation emission costs
                emH(k) = emH(k) + x(nonZ_r(i), nonZ_c(i))*distance(nonZ_r(i),
nonZ_c(i))*user_TransportationEmissions(nonZ_r(i), nonZ_c(i),k);
            end
        end
        %Sum values w/ weighting factor into final cost
        for j = 1:length(emissionGoals)
            EC = EC + weightF*(1-(emH(j)/emissionGoals(j)));
        end
    end
end

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```

```

function [CI] = FlowBasedMetrics_CI(Matrix, ga, x6)
%Flow Based Metrics Calculations
% 'Finn Cycling Index','Mean Path Length','Average Mutual
Information','Ascendency','Developmental Capacity','Total System Overhead','Alpha',
'Robustness', 'Shannon Index'

%===== Flow Based Metrics =====
% FLOW MATRIX
% Enter flow matrix [T] below and uncomment
% Must be a square matrix of size (N+3) x (N+3) where N represents the number of actors in the
system
% Flow is documented as moving from row (i) to column (j). The entry in row i and column j would
be denoted as tij.
% Row 0 represents imports from outside the system
% Rows 1 through N represent exchanges inside the system between actors
% Columns N+1 and N+2 represent exports to outside the system. Column N+1 is usable exports
(still have value) and Column N+2 is unusable (all value is gone)
% Rows N+1 and N+2 should be empty
% Column 0 should be empty
% for example: T = [ 0 288.6 806.4 0 0 0 ;...
%                 0 0 557.7 0 0 0 ;...
%                 0 0 0 1364 0 0 ;...
%                 0 269.1 0 0 1530.2 0 ;...
%                 0 0 0 0 0 0 ;...
%                 0 0 0 0 0 0 ];

% if(det(Matrix) ==0)
%     CI=-5;
%     return
% end
if ga == 1
    T = reshape(Matrix,size(x6));
else
    T = round(Matrix,3); % Enter flow matrix [T] here and UNCOMMENT this line
end
T = round(T,3); % Enter flow matrix [T] here and UNCOMMENT this line

n_T = size(T,1); %number of columns

num_Actors = size(Matrix,1);
%number of predators for each prey
com_row_sum = sum(Matrix,2);
%number of prey for each predator
com_col_sum = sum(Matrix);

%number of prey
num_Prey = nnz(com_row_sum);
%number of predators
num_Pred = nnz(com_col_sum);

flowAg = zeros(2,num_Actors);
for i = 1:length(com_col_sum)
    %Individual Generalization

```

```

    flowAg(1,i) = sum(com_col_sum(i))/num_Pred;
    %Individual Vulnerability
    flowAg(2,i) = sum(com_row_sum(i))/num_Prey;
end
%Total system throughPUT

P = T'; %flow is column to row for P matrix
P_rsum=sum(P,2); %sum over rows - get column vector P(i)
%P_csum=sum(P,1); %sum over columns - get row vector P(j)

%INSTANTANEOUS FRACTIONAL FLOW MATRIX CREATION (Q)
%INITIALIZING VARIABLES:
Q=zeros(n_T); %Instantaneous fractional flow matrix
i=1; %counter for the fractional flow matrix creation routine
%Converts the production matrix to the fractional flow matrix by dividing
%each element of a nonzero row by the sum of the row's elements
while i < n_T+1 %loop divides each row of P by its row sum
    try
        if P_rsum(i) > 0 %if statement prevents division when row sum = 0
            Q(i,:) = P(i,:)/P_rsum(i);
        end
        i=i+1;
    catch
        disp('problem')
    end
end

%TRANSITIVE CLOSURE MATRIX CREATION (N)
%Calculates the transitive closure matrix using the previously calculated
%fractional flow matrix => N=(I-Q)^-1
% warning('off','MATLAB:singularMatrix')
I=eye(size(P,1));
A=I-Q;
N1=A\I;

%N1 = inv(eye(size(P,1))-Q);

%%PRoblem occurs here when Matrix is found to be singular or close to
%%it. Trying to find a way to calculate the inverse without stupid
%%results. Possible solution is to add small values to matrix diagonal,
%%but I have not tried yet.
if isnan(sum(N1))
    disp('problem!!!');
    CI = 0;
    return
end

if isinf(N1)
    disp('PROBLEM');
    N1 = pinv(eye(size(P,1))-Q);
end

%FLOW METRIC CALCULATION (Warning: this code is problem dependent)
%Mean path length

```

```

inflow = sum(T(1,:)); %flow entering the system
internal_flow = sum(sum(T(2:(n_T-2),2:(n_T-2))));
TST = inflow + internal_flow; %total system throughflow (inflow + interholon flow)

%Mean cyclic path length
d_N = diag(N1); %diagonal elements of the N matrix
c_re = (d_N(2:(n_T-2))-ones(size(d_N(2:(n_T-2))))) ./ d_N(2:(n_T-2)); %return cycling eff.
vector
tst_c = c_re*P_rsum(2:(n_T-2));
%pl_c = tst_c/inflow;

%Finn Cycling Index (CI)
CI = tst_c/TST;

end

```

```

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```

```

function [x, Fval, output] =
runOpt(x6,x7,x8,x9,x10,x0,lb,ub,w1,w2,user_Emissions,user_TransportationEmissions,ga)
%This set of equalities says that the matrix inputs must match the
%matrix outputs. Otherwise, there will be errors in the ecological
%metrics calculations. Simply, this balances the matrix, not
%letting the optimization change values indiscriminantly
%without first considering the balancing of the matrix.

%Find size of matrix to loop through
[~,column] = size(x0);
%Set up counter
indexer = 1;
%Pre-allocate Equality matrices. These follow the form A*x=b and
%Aeq*x=beq
%See: https://www.mathworks.com/help/optim/ug/fmincon.html
%and for Matrix arguments:
%https://www.mathworks.com/help/optim/ug/matrix-arguments.html
Aeq = zeros(column-3,numel(x0));
beq = zeros(1,column-3);

%Loop through each of the actors columns setting the cell values of
%Imports+CellValue+Sum of rest of rows in column-sum of
%outgoing columns must == 0
for kk= 2:column-2
    %Prescribe zeros to the size of matrix
    AeqStart = zeros(size(x0));
    %Set Import of row = 1
    AeqStart(1,kk) = 1;
    %Set the entire column of actor = 1
    AeqStart(2:end,kk) = 1;
    %Subtract entire row of actor
    AeqStart(kk,2:end) = -1;
    %If any flow is going to itself, set = 0
    AeqStart(kk,kk)= 0;

```

```

    %Add result to container and start the next actor
    Aeq(indexer,:) = AeqStart(:);
    %Increase counter
    indexer = indexer + 1;
end

%This additional inequality says that the total exports of the
%system should remain the same after optimization is complete. That
%way, the productivity of the system is not lost.

%counter
indexer = 1;
%Preallocate export list
Aineq = zeros(column-3,numel(x0));
%Add initial user supplied values to equate these exports to
bineq = -1.*x0(2:end-2,end);
for kk = 2:column-2
    %Create matrix to do work on and
    %Clear from previous iteration
    AineqStart = zeros(size(x0));
    %trim list to only exports (Last column)
    AineqStart(kk,end) = -1;
    %List of one to the exports column
    Aineq(indexer,:) = AineqStart(:);
    %Increase counter
    indexer = indexer + 1;
end

if ga == 1
    %%
    %Genetic Algorithm Test
    options =
optimoptions(@gamultiobj,'PlotFcn',{@gaplotpareto,@gaplotscorediversity},'Display','iter','Populat
ionSize',6*numel(x0));
    [x,Fval,~,output] =
gamultiobj(@(x)objfun(x,ga),numel(x0),Aineq,bineq,Aeq,beq,lb(:),ub(:),[],options);
else
    %Options for fmincon optimization. Uses interior-point algorithm,
    %displaying results to console with an increased function eval. limit
    Fminconoptions = optimoptions('fmincon','Algorithm','interior-point','Display'...
    , 'iter','MaxFunctionEvaluations', 50000, 'ConstraintTolerance', 1e-6);

    %Optimization call to objective function using lower & upper bounds,
    %linear inequality and equality constraints, initial starting guess, and
    %options to the solver.
    [x,Fval,~,output] =
fmincon(@(x)objfun(x,ga),x0,Aineq,bineq,Aeq,beq,lb,ub,[],Fminconoptions);
end
%Objective function
function f = objfun(x, ga)
    %Genetic Algorithm Test
    if ga == 1
        f(1) = -FlowBasedMetrics_CI(x,ga,x6);
        f(2) = SystemCost(x, x6, x7, x8,x9,x10,ga);
    else

```

```

    %The first function is the Finn Cycling Index Ecosystem Metric
    f1 = FlowBasedMetrics_CI(x,ga,x6);
    %Scaling factor of FCI where max value is 1
    sf1 = 1;
    %The second function is the Total System Cost
    f2 = (1/13)*(1-(SystemCost(x, x6, x7, x8,x9,x10,ga)/5.9E6)) + EmissionsCost(x,
x9,user_Emissions,user_TransportationEmissions,ga);
    sf2 = SystemCost(ub./5, x6, x7, x8,x9,x10,ga) + EmissionsCost(ub./5,
x9,user_Emissions,user_TransportationEmissions, ga);
    %Scaling factor of total system cost
    %Maximize FCI while minimizing SystemCost and emissions
    f = -((w1/sf1)*f1)+((w2)*f2);
    %f = -((w1)*f1)+((w2)*f2);
end
end
end

```

```

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```

```

function [SC] = SystemCost(x, x6, x7, x8, x9, x10, ga)
if ga == 1
    x = reshape(x,size(x6));
end
%Speed up process by only looping over only non-zero records
[nonZ_r, nonZ_c] = find(x7);
%initialize System Cost
SC = 0;

%Find all non-zero elements in matrix and add the EnergyAmount in 1st
%dimension and energy cost in the second dimension to total system
%cost
if ~isempty(nonZ_r)
    for i = 1:length(nonZ_r)
        SC = SC + x(nonZ_r(i), nonZ_c(i))*x7(nonZ_r(i), nonZ_c(i))*...
            x8(nonZ_r(i), nonZ_c(i));
    end
end

%Speed up process by only looping over non-zero records
[nonZ_r, nonZ_c] = find(x6);

%Next add the cost of imported materials. Loop through all imported
%materials and add them to the total system cost by multiplying by flow
%amount
if ~isempty(nonZ_r)
    for k = 1:length(nonZ_r)
        SC = SC + x6(nonZ_r(k), nonZ_c(k))*x(nonZ_r(k)...
            , nonZ_c(k));
    end
end

%incorporate costs associated with the transportation of material

```

```

%Speed up process by only looping over non-zero records
[nonZ_r, nonZ_c] = find(x9);

%Next multiply the distance by the cost of transportation by the flow
%to get the total cost of transportation and add this to the system
%cost
if ~isempty(nonZ_r)
    for i = 1:length(nonZ_r)
        SC = SC + x(nonZ_r(i), nonZ_c(i))*x9(nonZ_r(i), nonZ_c(i))*...
            x10(nonZ_r(i), nonZ_c(i));
    end
end

%incorporate penalties for dissipative losses by multiplying the
%dissipative flows by the cost of emitting said flow

% [nonZ_r, nonZ_c] = find(x10);
% if ~isempty(nonZ_r)
%     for k = 1:length(nonZ_r)
%         SC = SC + x10(nonZ_r(k), nonZ_c(k))*x(nonZ_r(k)...
%             , nonZ_c(k));
%     end
% end

%incorporate embodied energy savings

end

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function [] = optimization_Class
%%User Inputted Data
%Initial Flow Amounts to and from system components (or reasonable
%approximation) Must be a square matrix of size (N+3) x (N+3) where N
%represents the number of actors in the system
%Flow is documented as moving from row (i) to column (j).
%The entry in row i and column j would be denoted as tij.
% Row 0 represents imports from outside the system
% Rows 1 through N represent exchanges inside the system between actors
% Columns N+1 and N+2 represent exports to outside the system.
%Column N+1 is usable exports (still have value) and Column N+2 is
%unusable (all value is gone)
% Rows N+1 and N+2 should be empty
% Column 0 should be empty
% for example: T = [ 0 288.6 806.4 0 0 0 ;...
%     0 0 557.7 0 0 0 ;...
%     0 0 0 1364 0 0 ;...
%     0 269.1 0 0 1530.2 0 ;...
%     0 0 0 0 0 0 ;...
%     0 0 0 0 0 0 ];

```

```
user_InputFlowMatrix = ...
```

235


```

0 0 0 0 0 0 0 0 0 0 0 0 0 0 14834 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 1648 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 12733 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 1415 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 316635;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 88298;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 33306;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 248585;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 528682;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 219683;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 44553;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 26174;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 427355;
0 797729 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 341884 0 284903 0 0;
0 199432 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 85471 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0];

```

% N+3xN+3 Fake Data for minimum flows each component needs

user_InputMinFlowMatrix = ...

```

[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0];

```

237

```

0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0];

```

```

%Storage limitations to system components. This should be a of N+3xN+3 in
%length specifying the maximum amount (constraint) of material storage
%each component can accrue.
%Oyster Reef Natural Ecosystem Data
% user_InputStorageMatrix = ...
% [0 0 0 0 0 0 0 0 0;
% 200 0 0 0 0 0 0 0 0;
% 2.4121 0 0 0 0 0 0 0 0;
% 24.121 0 0 0 0 0 0 0 0;
% 16.274 0 0 0 0 0 0 0 0;
% 69.237 0 0 0 0 0 0 0 0;
% 100 0 0 0 0 0 0 0 0;
% 0 0 0 0 0 0 0 0;
% 0 0 0 0 0 0 0 0];

```

```

%This should be a N+3xN+3 matrix specifying the distance limitations of a
%system component to donstream component. i.e. Flow i to j has a distance
%limitation of 150 meters
%Fake Data

```

```

user_InputDistanceMatrix = ...
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 166 100 134 50 121 103 84 172 108 159 134 146 138 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 21 0 0
0 0 0 0 0 0 166 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 11 0
0 0 0 0 0 0 100 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 56 0 0
0 0 0 0 0 0 134 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 8
0 0 0 0 0 0 50 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
19 0 0 0 0 0 121 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 34 0 0 0 0 103 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 63 0 0 0 0 84 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 31 0 0
0 0 0 0 0 0 172 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 8 0 0 0 0 108 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 21 0 0 0 159 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 29 0 0 134 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 48 0 0 0 0 146 0 0 0;

```

```
% user_InputDistanceMatrix(:, :, 2) = ...
```

```
% [0 0 0 0 0 0 0 0 0;
% 0 0 0 0 0 100 500 0 0;
% 0 0 0 100 50 0 0 0 0;
% 0 0 0 0 50 0 100 0 0;
% 0 0 0 0 0 100 150 0 0;
% 0 0 0 0 0 0 50 0 0;
% 0 0 500 150 100 0 0 0 0;
% 0 0 0 0 0 0 0 0 0;
% 0 0 0 0 0 0 0 0 0];
```

%This is a NxN length vector specifying the initial cost of a specific
%import per unit i.e. \$/kg or \$/kWh
%Fake Data

```
user_ImportMaterialCostMatrix = ...
```

[illegible]

242

%This is a N+3xN+3x2 matrix that specifies if a specific dissipation is
%recoverable or not due to quality. The first dimension is 0 or 1 depending
%if the dissipation is recoverable, while the second dimension shows the cost
%of emitting to the environment
%Fake Data. No dissipative flows in Oyster Reef Ecosystem so blank.

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
0 0 0 0 0 0 0 0 0 0 0;  
0 0 0.002372022 0.002372022 0.002372022 0.002372022 0.002372022 0.002372022  
0.002372022 0.002372022 0.002372022 0.002372022 0.002372022 0.002372022 0.002372022  
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0;  
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.002372022 0 0 0 0 0 0 0 0 0 0 0 0  
0.002372022 0 0 0 0 0 0 0 0 0.002372022 0 0 0;  
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.002372022 0 0 0 0 0 0 0 0 0 0 0 0  
0 0.002372022 0 0 0 0 0 0 0 0.002372022 0 0 0;  
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.002372022 0 0 0 0 0 0 0 0 0 0 0  
0.002372022 0 0 0 0 0 0 0 0 0.002372022 0 0 0;  
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.002372022 0 0 0 0 0 0 0 0 0 0 0  
0 0 0.002372022 0 0 0 0 0 0 0.002372022 0 0 0;  
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.002372022 0 0 0 0 0 0 0 0 0  
0 0 0 0.002372022 0 0 0 0 0.002372022 0 0 0;  
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.002372022 0 0 0 0 0 0 0  
0 0 0 0 0.002372022 0 0 0 0 0.002372022 0 0 0;  
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.002372022 0 0 0 0 0 0  
0.002372022 0 0 0 0 0 0 0 0 0.002372022 0 0 0;  
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.002372022 0 0 0 0  
0 0 0 0 0.002372022 0 0 0 0.002372022 0 0 0;  
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.002372022 0 0  
0 0 0 0 0 0.002372022 0 0 0 0.002372022 0 0 0;  
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
0.002372022 0 0 0 0 0 0 0 0.002372022 0 0.002372022 0 0 0;
```

% Transportation emissions matrix (kg CO2/km-kg)
user TransportationEmissions = ...

[illegible]

```

0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.000716569 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0.000716569 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0.000716569 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0.000716569 0 0.000144117 0 0;
0 0.000144117 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0.000716569 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0];

```

% Emissions matrix (CO2 kg/kg)

user_Emissions = ...

```

[0 2.9482 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0.188085682 0.188085682 0.188085682 0.188085682 0.188085682 0.188085682
0.188085682 0.188085682 0.188085682 0.188085682 0.188085682 0.188085682 0.188085682
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0
0 0 0 0 0 0 0.18320778 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0
0 0 0 0 0 0 0.18320778 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0
0 0 0 0 0 0 0.18320778 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
0 0 0 0 0 0 0.18320778 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
1 0 0 0 0 0 0.18320778 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 1 0 0 0 0 0.18320778 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 1 0 0 0 0 0.18320778 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 1 0 0 0 0 0.18320778 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 1 0 0 0 0.18320778 0 0 0;

```

249

252

[illegible]

[illegible]

255

```

0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0.000413 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0.008834896 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0];

```

%NOx

user_Emissions(:,5) = ...

```

[0 0.010314 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0.000160083 0.000160083 0.000160083 0.000160083 0.000160083 0.000160083
0.000160083 0.000160083 0.000160083 0.000160083 0.000160083 0.000160083 0.000160083
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0.00022407 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0.00022407 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0.00022407 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0.00022407 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0.00022407 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0.00022407 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0.00022407 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0.00022407 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0.00022407 0 0 0;
0 0 1.79E-08 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 1.7872E-08 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 1.7872E-08 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 1.7872E-08 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 1.7872E-08 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0];

```

[illegible]

258

[illegible]

261

```
%Hg
user_Emissions(:,9) = ...
[0 2.48E-08 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 1.39917E-09 1.39917E-09 1.39917E-09 1.39917E-09 1.39917E-09 1.39917E-09
1.39917E-09 1.39917E-09 1.39917E-09 1.39917E-09 1.39917E-09 1.39917E-09 1.39917E-09 1.39917E-09 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 1.95843E-09 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 1.95843E-09 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 1.95843E-09 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 1.95843E-09 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 1.95843E-09 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 1.95843E-09 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 1.95843E-09 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 1.56E-13 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
```

[illegible]

264

[illegible]

%SO_x

[illegible]

269

272

```

0 4.41014E-09 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 4.41014E-09 0 4.89916E-10 0 0;
0 4.89916E-10 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 4.41014E-09 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0];

```

%SO2

```

user_TransportationEmissions(:,4) = ...

```

```

[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 8.96729E-09 8.96729E-09 8.96729E-09 8.96729E-09 8.96729E-09 8.96729E-09
8.96729E-09 8.96729E-09 8.96729E-09 8.96729E-09 8.96729E-09 8.96729E-09 8.96729E-09 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 8.96729E-09 0 0 0 0 0 0 0 0 0 0
8.96729E-09 0 0 0 0 0 0 0 0 8.96729E-09 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 8.96729E-09 0 0 0 0 0 0 0 0
0 8.96729E-09 0 0 0 0 0 0 0 8.96729E-09 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 8.96729E-09 0 0 0 0 0 0 0 0
8.96729E-09 0 0 0 0 0 0 0 8.96729E-09 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 8.96729E-09 0 0 0 0 0 0 0 0
0 0 8.96729E-09 0 0 0 0 0 8.96729E-09 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 8.96729E-09 0 0 0 0 0 0 0
0 0 0 8.96729E-09 0 0 0 0 8.96729E-09 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 8.96729E-09 0 0 0 0 0
0 0 0 0 8.96729E-09 0 0 0 0 8.96729E-09 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 8.96729E-09 0 0 0 0
8.96729E-09 0 0 0 0 0 0 0 8.96729E-09 0 0 0;
0 0 8.96729E-09 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
8.96729E-09 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 8.96729E-09 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 8.96729E-09 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 8.96729E-09 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
8.96729E-09 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 8.96729E-09 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 8.96729E-09 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 8.96729E-09 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 8.96729E-09 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 8.96729E-09 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 8.96729E-09 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 8.96729E-09 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 8.96729E-09 0 0 0 0 0 0 0;

```


275


```

0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 4.49835E-06 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 4.49835E-06 0 1.06475E-06 0 0;
0 1.06475E-06 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 4.49835E-06 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0];

```

%Pb

user_TransportationEmissions(:,6) = ...

```

[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0];

```

```
%CO  
user_TransportationEmissions(:,7) = ...  
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
0 0 0 0 0 0 0 0 0 0 0;  
0 0 1.74495E-05 1.74495E-05 1.74495E-05 1.74495E-05 1.74495E-05 1.74495E-05  
1.74495E-05 1.74495E-05 1.74495E-05 1.74495E-05 1.74495E-05 1.74495E-05 1.74495E-05 1.74495E-05  
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0;  
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1.74495E-05 0 0 0 0 0 0 0 0 0 0 0 0  
1.74495E-05 0 0 0 0 0 0 0 0 1.74495E-05 0 0 0;  
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1.74495E-05 0 0 0 0 0 0 0 0 0 0  
0 1.74495E-05 0 0 0 0 0 0 0 1.74495E-05 0 0 0;  
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1.74495E-05 0 0 0 0 0 0 0 0 0 0  
1.74495E-05 0 0 0 0 0 0 0 0 1.74495E-05 0 0 0;
```

278

```

0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 1.74495E-05 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 1.74495E-05 0 4.12509E-06 0 0;
0 4.12509E-06 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 1.74495E-05 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0];

```

%VOCs

```
user_TransportationEmissions(:,8) = ...
```

```

[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0];

```


281

```

0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0];

```

%HC

```
user_TransportationEmissions(:,10) = ...
```

```

[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 1.47005E-06 1.47005E-06 1.47005E-06 1.47005E-06 1.47005E-06 1.47005E-06
1.47005E-06 1.47005E-06 1.47005E-06 1.47005E-06 1.47005E-06 1.47005E-06 1.47005E-06 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1.47005E-06 0 0 0 0 0 0 0 0 0 0 0 0
1.47005E-06 0 0 0 0 0 0 0 0 1.47005E-06 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1.47005E-06 0 0 0 0 0 0 0 0 0 0 0 0
0 1.47005E-06 0 0 0 0 0 0 0 1.47005E-06 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1.47005E-06 0 0 0 0 0 0 0 0 0 0
1.47005E-06 0 0 0 0 0 0 0 0 1.47005E-06 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1.47005E-06 0 0 0 0 0 0 0 0 0 0
0 0 1.47005E-06 0 0 0 0 0 0 1.47005E-06 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1.47005E-06 0 0 0 0 0 0 0 0
0 0 0 0 1.47005E-06 0 0 0 0 1.47005E-06 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1.47005E-06 0 0 0 0 0 0
0 0 0 0 1.47005E-06 0 0 0 0 1.47005E-06 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1.47005E-06 0 0 0 0 0 0
1.47005E-06 0 0 0 0 0 0 0 0 1.47005E-06 0 0 0;
0 0 1.47005E-06 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
1.47005E-06 0 0 0 0 0 0 0 0 0 0 0 0;

```

[illegible]

284

```

0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 1.17604E-07 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 1.17604E-07 0 2.61288E-08 0 0;
0 2.61288E-08 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 1.17604E-07 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0];

```

%SOx

user_TransportationEmissions(:,12) = ...

```

[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0;
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0];

```

286

```

0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0];

```

```
%%
```

```

%NEED: A way to identify if a specific flow could be used in other system
%components. We could identify all the flows from the initial flow matrix
%and what component they are going to and use that as the flow identifier

```

```

%NEED: Identify how we want to incorporate storage. There's a couple of
%storage analysis metrics on :
%https://cran.r-project.org/web/packages/enaR/vignettes/enaR-vignette.pdf
%We could use one or some of these, but we must identify the most useful.

```

```

%NEED: Incorporate embodied energy into flow metrics to impact energy
%requirement of specific component. Could increase or decrease energy
%demand depending on flow properties

```

```

%NEED: Incorporate rates into the flows to system components. Right now
%they're steady state.

```

```
%GA Test
```

```
ga =0;
```

```

%This is a check if user-inputted model is steady state or not.
%Will throw warning if not steady-state.
steadyStateCheck(user_InputFlowMatrix);

```

```
%Set Lower Bounds
```

```
%Only minimum flow values are taken into account currently
```

```
lb = user_InputMinFlowMatrix;
```

```
%LB Still Need:
```

```
%Minimum distances between components (user supplied)
```

```
%Minimum Storage (0)
```

```
%Set Upper Bounds
```

```
%10x the maximum flow value are taken into account currently
```

```
%Maximum Flow Values
```

```
%First find the maximum value in total matrix and multiply by ten
```

```
ub = max(max(user_InputFlowMatrix))*10*full(spones(user_InputFlowMatrix));
```

```
%Still Need:
```

```
%Maximum flow values based on storage constraint
```

```
%Maximum distances between components (user supplied)
```

```
%Maximum Storage (User Supplied)
```

```
%Calculate initial function value of user-supplied data assuming equal
```

```
%weighting
```

```
initsox = FlowBasedMetrics_CI(user_InputFlowMatrix, ga,...
```

```

    user_ImportMaterialCostMatrix);
initsoly1 = SystemCost(user_InputFlowMatrix, user_ImportMaterialCostMatrix,...
    user_ComponentConversionEnergyCost(:,1),...
    user_ComponentConversionEnergyCost(:,2),...
    user_InputDistanceMatrix(:,1),...
    user_TransportationCosts, ga);
initsoly2 = EmissionsCost(user_InputFlowMatrix, user_InputDistanceMatrix(:,1),...
    user_Emissions,user_TransportationEmissions,ga);
initFval = -0.5*initsolx+0.5*(initsoly1+initsoly2);

%Initialize Counter
j=1;

[rown, coln] = size(user_InputFlowMatrix);

%Pre-allocate for storing optimization results
solx = zeros(1,51);
soly = zeros(1,51);
solz = zeros(1,51);
minx = zeros(rown,coln,51);

if ga == 1
    %Run optimization with supplied weights
    [x,Fval] = runOpt(user_ImportMaterialCostMatrix,...
        user_ComponentConversionEnergyCost(:,1),...
        user_ComponentConversionEnergyCost(:,2)...
        ,user_Recovery(:,1),user_Recovery(:,2)...
        ,user_InputFlowMatrix,lb,ub,1,1,ga);
    disp(x);
    disp(Fval);
    y = reshape(round(x(1,:),4),size(user_InputFlowMatrix));
else
    %Loop through at 0.2 increment from 0 up to 1 for both weights
    % for i = 0:0.02:1
    % Vary weights throughout loop to generate pareto curve
    % w1 = i;
    % w2 = 1-i;
    w1 = 0;
    w2 = 1;

    %Run optimization with supplied weights
    [x,Fval] = runOpt(user_ImportMaterialCostMatrix,...
        user_ComponentConversionEnergyCost(:,1),...
        user_ComponentConversionEnergyCost(:,2)...
        ,user_InputDistanceMatrix(:,1),user_TransportationCosts...
        ,user_InputFlowMatrix,lb,ub,w1,w2,user_Emissions,user_TransportationEmissions, ga);

    %Solution to optimization problem at specified weighted sums
    solx(j) = FlowBasedMetrics_CI(x,ga,user_ImportMaterialCostMatrix);
    soly(j) = SystemCost(x, user_ImportMaterialCostMatrix,...
        user_ComponentConversionEnergyCost(:,1),...
        user_ComponentConversionEnergyCost(:,2),...

```

```

        user_InputDistanceMatrix(:,j,1),...
        user_TransportationCosts, ga);
    solz(j) = Fval;
    minx(:,j) = x;
    %Increase counter
    j=j+1;
end

%Plot PAreto Curve and axis labels
scatter3(solx, soly, solz);
xlabel('FCI')
ylabel('System Cost')
zlabel('OBJ Function Value')

%Generate User Output to Console
%Initial matrix
disp(user_InputFlowMatrix);
%Initial value of function
fprintf('The initial objective functions value was %f \n', initFval);
%Final objective function value
[minval, minindx] = min(solz);
fprintf('The final objective functions value was %f \n', minval);
disp(minx(:,minindx));
%Check if final matrix has satisfied steady-state constraint
steadyStateCheck(minx(:,minindx));
%end
end

%Function that checks if inputted model is steady state
function Flow_Matrix_Balanced = steadyStateCheck(T)
%Adapted from Fath, Borrett 2005
%A MATLAB function for Network Environ Analysis
Flow_Matrix = T(2:end-2,2:end-2);
%inputs
z = T(1,2:end-2)';
%respiration
r = T(2:end-2,end);
%exports
e = T(2:end-2,end-1);

%combined exports and respiration
y = sum([e,r],2);

%Sum of flow matrix column plus imports (z)
Tin = sum(Flow_Matrix,1)+z;
%Sum of individual row plus outputs (y) ( y = Respiration(r) + Exports(e))
Tout = sum(Flow_Matrix,2)+y;

pd = abs((Tin - Tout))./Tin;
pd_count = length(find(pd>=0.0005));

```

```

if pd_count == 0
    steady = 1;
else
    steady = 0;
    warning('Model is NOT Steady State');
end

if steady
    Flow_Matrix_Balanced = T;
    %disp('end')
else
    %Adapted from S. Allesina, C. Bondavalli
    %Steady state of ecosystem flow networks: a comparison between
    %balancing procedures
    %Ecological Modelling, 165 (2003), pp. 221\96229

    %Step 1 - Completed
    %Step 2 - Divide all coefficients tij by the ith-row sum to obtain
    %F*[fij*]

    %combine Flow Matrix with Respiration and Exports
    comb_in = [Flow_Matrix, e, r];
    F_star = bsxfun(@rdivide,comb_in,Tout);

    %For output
    comb_out = [Flow_Matrix', z];
    F_star_out = bsxfun(@rdivide,comb_out,Tin);
    %InCase any dividing by zero occurred (MATLAB puts NaN which will mess
    %everything up later)
    F_star_out(isnan(F_star_out)) = 0;
    F_star(isnan(F_star)) = 0;

    %Step 3 - Transpose NxN part of Matrix F_star and subtract the identity
    %matrix to get R
    %Step 4 - Invert R
    R_in = inv(F_star(:,1:end-2)' - eye(length(F_star(:,1:end-2))));
    R_out = inv(F_star_out(:,1:end-1)' - eye(length(F_star_out(:,1:end-1))));

    %Step 5 - Multiple every coefficient in rij by the corresponding jth
    %input in the Flow_Matrix and then change it's sign
    R_in = -bsxfun(@times,R_in,z');
    R_out = -bsxfun(@times,R_out,y');

    %Step 6 - Sum ith's row to build vector U
    U = sum(R_in,2);
    U_out = sum(R_out,2);

    %Step 7 - Multiply each F_star_ij by the corresponding ui to obtain a
    %balanced form Flow_Matrix_Balanced
    %Invert matrix again for TBalOut
    TBalln = bsxfun(@times,F_star,U);
    TBalOut = (bsxfun(@times,F_star_out,U_out))';

```

```

%Combine Balanced_In Matrix with Imports
Flow_Matrix_Format_in = [T(1,2:end);TBalIn; zeros(2,length(T(1,2:end)))];
%Algorithm 1
Flow_Matrix_Balanced_In = [zeros(length(Flow_Matrix_Format_in),1),
Flow_Matrix_Format_in];

%Combine Balanced_Out with exports and respiration
[~,c] = size(TBalOut);
[r,~] = size(T);
Flow_Matrix_Format_out = [circshift(TBalOut,1); zeros(2,c)];
Flow_Matrix_Format_out = [zeros(r,1), Flow_Matrix_Format_out];
[~,c1] = size(Flow_Matrix_Format_out);
%Algorithm 2
Flow_Matrix_Balanced_Out = [Flow_Matrix_Format_out, T(:,c1+1:end)];

%%AVG2
%%
%T_IO_Bal
%Add 1/2T_in_Bal to 1/2 T_Star
%Added_IO = bsxfun(@plus, 0.5.*Flow_Matrix_Balanced_In, 0.5.*T);
%Algorithm 3
%T_IO_BAL = bsxfun(@times,Flow_Matrix_Balanced_Out,Added_IO);

%Add 1/2 T_out_Bal to 1/2 T_Star and multiply result by T*inBal
%Added_OI = bsxfun(@plus, 0.5.*Flow_Matrix_Balanced_Out, 0.5.*T);
%Algorithm 4
%T_OI_BAL = bsxfun(@times,Flow_Matrix_Balanced_In,Added_OI);

%Algorithm 5
T_Bal_AVG = 0.5.*bsxfun(@plus,Flow_Matrix_Balanced_In,Flow_Matrix_Balanced_Out);
Flow_Matrix_Balanced = T_Bal_AVG;
%Algorithm 6
%T_Bal_AVG2 = 0.5.*bsxfun(@plus,T_IO_BAL,T_OI_BAL);

end
end

```

C.2 Automotive Case Study Network Structures

Energy

Current

Table 30. Current Water Network of Automotive Case Study

From	Component	To									
		1	2	3	4	5	6	7	8	9	10
1	Municipal Reservoir	0	1	0	0	0	0	0	0	0	0
2	Municipal Distribution	0	0	0	1	1	1	1	0	0	0

3	Municipal WWT	0	1	0	0	0	0	0	0	0
4	Residential	0	0	1	0	0	0	0	0	0
5	Local Suppliers	0	0	1	0	0	0	0	0	0
6	Agriculture	0	0	1	0	0	0	0	0	0
7	Automotive Manufacturing Plant	0	0	1	0	0	0	0	0	1
8	Automotive Manufacturing Reservoir	0	0	0	0	0	0	0	0	0
9	Automotive Water Distribution	0	0	0	0	0	0	0	0	0
10	Automotive Wastewater Treatment	0	0	1	0	0	0	0	0	0

Rain Capture

Table 31. Automotive Water Network with Rainwater Capture

	Component	To									
		1	2	3	4	5	6	7	8	9	10
From	1 Municipal Reservoir	0	1	0	0	0	0	0	0	0	0
	2 Municipal Distribution	0	0	0	1	1	1	1	0	0	0
	3 Municipal WWT	0	1	0	0	0	0	0	0	0	0
	4 Residential	0	0	1	0	0	0	0	0	0	0
	5 Local Suppliers	0	0	1	0	0	0	0	0	0	0
	6 Agriculture	0	0	1	0	0	0	0	0	0	0
	7 Automotive Manufacturing Plant	0	0	1	0	0	0	0	0	0	1
	8 Automotive Manufacturing Reservoir	0	0	0	0	0	0	0	0	1	0
	9 Automotive Water Distribution	0	0	0	0	0	0	1	0	0	0
	10 Automotive Wastewater Treatment	0	0	1	0	0	0	0	0	0	0

Gray Water

Table 32. Automotive Water Network with Graywater Systems

	Component	To									
		1	2	3	4	5	6	7	8	9	10
From	1 Municipal Reservoir	0	1	0	0	0	0	0	0	0	0
	2 Municipal Distribution	0	0	0	1	1	1	1	0	0	0
	3 Municipal WWT	0	1	0	0	0	0	0	0	0	0
	4 Residential	0	0	1	0	0	0	0	0	0	0
	5 Local Suppliers	0	0	1	0	0	0	0	0	0	0
	6 Agriculture	0	0	1	0	0	0	0	0	0	0

7	Automotive Manufacturing Plant	0	0	1	0	0	0	0	0	1
8	Automotive Manufacturing Reservoir	0	0	0	0	0	0	0	0	0
9	Automotive Water Distribution	0	0	0	0	0	1	0	0	0
10	Automotive Wastewater Treatment	0	0	1	0	0	0	0	1	0

Community (All)

Table 33. Automotive Water Network with All Scenarios and Community Integration

	From	Component	To									
			1	2	3	4	5	6	7	8	9	10
	1	Municipal Reservoir	0	1	0	0	0	0	0	0	0	0
	2	Municipal Distribution	0	0	0	1	1	1	1	0	0	0
	3	Municipal WWT	0	1	0	0	0	0	0	0	0	0
	4	Residential	0	0	1	0	0	0	0	0	0	1
	5	Local Suppliers	0	0	1	0	0	0	0	0	0	1
	6	Agriculture	0	0	1	0	0	0	0	0	0	0
	7	Automotive Manufacturing Plant	0	0	1	0	0	0	0	0	0	1
	8	Automotive Manufacturing Reservoir	0	0	0	0	0	0	0	0	1	0
	9	Automotive Water Distribution	0	0	0	1	1	1	1	0	0	0
	10	Automotive Wastewater Treatment	0	0	1	0	0	0	0	1	0	0

Material

Current

Table 34. Automotive Material Network

Component	To									
	1	2	3	4	5	6	7	8	9	10

From	1	Automotive Manufacturing Plant	0	0	0	1	0	1	1	1	1	0
	2	Local Suppliers	1	0	0	0	0	1	0	0	0	0
	3	Non-Local Suppliers	1	0	0	0	0	0	0	0	0	0
	4	Residential	0	0	0	0	0	1	0	0	0	0
	5	Agriculture	1	1	0	1	0	1	0	0	0	0
	6	Landfill	0	0	0	0	0	0	0	0	0	0
	7	Paper Recycling	0	0	0	0	0	0	0	0	0	0
	8	Metal Recycling	0	0	0	0	0	0	0	0	0	0
	9	Wood Recycling	0	0	0	0	1	0	0	0	0	0
	10	Composting Facility	0	0	0	0	0	0	0	0	0	0

recycling

Table 35. Automotive Material Network with Recycling

			To									
			1	2	3	4	5	6	7	8	9	10
From	1	Automotive Manufacturing Plant	0	0	0	1	0	1	1	1	1	1
	2	Local Suppliers	1	0	0	0	0	1	1	1	1	1
	3	Non-Local Suppliers	1	0	0	0	0	0	0	0	0	0
	4	Residential	0	0	0	0	0	1	1	0	0	1
	5	Agriculture	1	1	0	1	0	1	0	0	1	1
	6	Landfill	0	0	0	0	0	0	0	0	0	0
	7	Paper Recycling	0	0	0	0	0	0	0	0	0	0
	8	Metal Recycling	0	0	0	0	0	0	0	0	0	0
	9	Wood Recycling	0	0	0	0	1	0	0	0	0	0
	10	Composting Facility	0	0	0	0	0	0	0	0	0	0

Closed loop recycling

Table 36. Automotive Material Network with Closed-Loop Recycling

	Component	To									
		1	2	3	4	5	6	7	8	9	10
From	1 Automotive Manufacturing Plant	0	0	0	1	0	1	1	1	1	1
	2 Local Suppliers	1	0	0	0	0	1	1	1	1	1
	3 Non-Local Suppliers	1	0	0	0	0	0	0	0	0	0
	4 Residential	0	0	0	0	0	1	1	0	0	1
	5 Agriculture	1	1	0	1	0	1	0	0	1	1
	6 Landfill	0	0	0	0	0	0	0	0	0	0
	7 Paper Recycling	1	1	0	1	0	0	0	0	0	0
	8 Metal Recycling	1	1	0	0	0	0	0	0	0	0
	9 Wood Recycling	1	1	0	0	1	0	0	0	0	0
	10 Composting Facility	1	1	0	1	1	0	0	0	0	0

Table 37. Current Automotive Energy Network

	Component	To													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
From	1 Electric Utility	0	1	0	1	0	1	1	1	0	0	1	1	1	1
	2 Natural Gas Utility	1	0	0	0	1	1	0	0	0	0	1	0	0	1
	3 Hydrogen Gas Supplier	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	4 Landfill	0	0	0	0	1	0	0	0	0	0	0	0	0	0
	5 Plant Energy Center	0	0	0	0	0	1	0	1	0	0	0	0	0	0
	6 Automotive Manufacturing Plant	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	7 Recycling/Composting	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	8 Plant Museum	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	9 PV Array	0	0	0	0	0	0	0	1	0	0	0	0	0	0
	10 Steam Reforming H2 Generator	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	11 Local Suppliers	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	12 Municipal Water Distribution	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	13 Agriculture	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	14 Residential	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Hydrogen Generation

Table 38. Automotive Energy Network with Hydrogen Generation

Component	To													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14

From	1	Electric Utility	0	1	0	1	0	1	1	1	0	0	1	1	1	1
	2	Natural Gas Utility	1	0	0	0	1	1	0	0	0	1	1	0	0	1
	3	Hydrogen Gas Supplier	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	4	Landfill	0	0	0	0	1	0	0	0	0	1	0	0	0	0
	5	Plant Energy Center	0	0	0	0	0	1	0	1	0	1	0	0	0	0
	6	Automotive Manufacturing Plant	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	7	Recycling/Composting	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	8	Plant Museum	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	9	PV Array	0	0	0	0	0	0	0	1	0	0	0	0	0	0
	10	Steam Reforming H2 Generator	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	11	Local Suppliers	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	12	Municipal Water Distribution	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	13	Agriculture	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	14	Residential	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Photovoltaics Expansion

Table 39. Automotive Energy Network with Photovoltaics Expansion

From	Component		To													
			1	2	3	4	5	6	7	8	9	10	11	12	13	14
	1	Electric Utility	0	1	0	1	0	1	1	1	0	0	1	1	1	1
	2	Natural Gas Utility	1	0	0	0	1	1	0	0	0	0	1	0	0	1
	3	Hydrogen Gas Supplier	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	4	Landfill	0	0	0	0	1	0	0	0	0	0	0	0	0	0
	5	Plant Energy Center	0	0	0	0	0	1	0	1	0	0	0	0	0	0
	6	Automotive Manufacturing Plant	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	7	Recycling/Composting	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	8	Plant Museum	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	9	PV Array	0	0	0	0	1	1	0	1	0	0	0	0	0	0
	10	Steam Reforming H2 Generator	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	11	Local Suppliers	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	12	Municipal Water Distribution	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	13	Agriculture	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	14	Residential	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Microgrid

Table 40. Automotive Energy Network with Microgrid Configuration

	Component	To													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
From	1 Electric Utility	0	1	0	1	0	1	1	1	0	0	1	1	1	1
	2 Natural Gas Utility	1	0	0	0	1	1	0	0	0	0	1	0	0	1
	3 Hydrogen Gas Supplier	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	4 Landfill	0	0	0	0	1	0	0	0	0	0	0	0	0	0
	5 Plant Energy Center	0	0	0	1	0	1	1	1	0	0	1	1	1	1
	6 Automotive Manufacturing Plant	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	7 Recycling/Composting	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	8 Plant Museum	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	9 PV Array	0	0	0	0	0	0	0	1	0	0	0	0	0	0
	10 Steam Reforming H2 Generator	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	11 Local Suppliers	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	12 Municipal Water Distribution	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	13 Agriculture	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	14 Residential	0	0	0	0	0	0	0	0	0	0	0	0	0	0

All

Table 41. Automotive Energy Network with All Energy Scenarios

	Component	To													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
From	1 Electric Utility	0	1	0	1	0	1	1	1	0	0	1	1	1	1
	2 Natural Gas Utility	1	0	0	0	1	1	0	0	0	1	1	0	0	1
	3 Hydrogen Gas Supplier	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	4 Landfill	0	0	0	0	1	0	0	0	0	1	0	0	0	0
	5 Plant Energy Center	0	0	0	1	0	1	1	1	0	1	1	1	1	1
	6 Automotive Manufacturing Plant	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	7 Recycling/Composting	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	8 Plant Museum	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	9 PV Array	0	0	0	0	1	1	0	1	0	0	0	0	0	0
	10 Steam Reforming H2 Generator	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	11 Local Suppliers	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	12 Municipal Water Distribution	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	13 Agriculture	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	14 Residential	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 42. Current Automotive Material, Water, and Energy Meta-Model

	Component	To																						
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
From	1 Municipal Water Reservoir	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	2 Municipal Water Distribution	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0
	3 Municipal Wastewater Treatment	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	4 Residential	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
	5 Local Suppliers	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
	6 Agriculture	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
	7 Automotive Manufacturing Plant	0	0	1	1	0	0	0	0	0	1	0	1	1	1	0	1	0	0	0	0	0	0	0
	8 Automotive Manufacturing Reservoir	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	9 Automotive Water Distributions	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	10 Automotive Wastewater Treatment	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	11 Non-Local Suppliers	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	12 Paper Recycling	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	13 Metal Recycling	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	14 Wood Recycling	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	15 Composting Facility	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	16 Landfill	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
	17 Electric Utility	0	1	1	1	1	1	1	0	0	1	0	1	1	1	0	1	0	1	0	0	1	0	0
	18 Natural Gas Utility	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0
	19 Hydrogen Gas Supplier	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	20 Plant Energy Center	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0
	21 Plant Museum	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	22 Photovoltaic Array	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	23 Steam Reforming H2 Generator	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 43. Best Case Automotive Meta-Model

	Component	To																						
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
From	1 Municipal Water Reservoir	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	2 Municipal Water Distribution	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0
	3 Municipal Wastewater Treatment	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	4 Residential	0	0	1	0	0	0	0	0	0	1	0	1	0	0	1	1	0	0	0	0	0	0	0
	5 Local Suppliers	0	0	1	0	0	0	1	0	0	1	0	1	1	1	1	1	0	0	0	0	0	0	0
	6 Agriculture	0	0	1	1	1	0	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0
	7 Automotive Manufacturing Plant	0	0	1	1	0	0	0	0	0	1	0	1	1	1	1	1	0	0	0	0	0	0	0
	8 Automotive Manufacturing Reservoir	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	9 Automotive Water Distributions	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	10 Automotive Wastewater Treatment	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	11 Non-Local Suppliers	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	12 Paper Recycling	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	13 Metal Recycling	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	14 Wood Recycling	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	15 Composting Facility	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	16 Landfill	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
	17 Electric Utility	0	1	1	1	1	1	1	0	0	1	0	1	1	1	1	1	0	1	0	0	1	0	0
	18 Natural Gas Utility	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	1
	19 Hydrogen Gas Supplier	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	20 Plant Energy Center	0	1	1	1	1	1	1	0	0	1	0	1	1	1	1	1	0	1	0	0	1	0	1
	21 Plant Museum	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	22 Photovoltaic Array	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
	23 Steam Reforming H2 Generator	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

APPENDIX D. STEEL WATER NETWORK

This appendix highlights the methods used to calculate the costs associated with the constructed wetlands and pyrolysis study in the Bioaugmentation of a Steel Water Network Using Constructed Wetlands and Pyrolysis Modeling chapter of this dissertation. The first section is the unsimplified structure of the steel industry water network used in our analysis. The second section shows the calculations for the universal parameter discussed in the study and pyrolysis char yield. The third section gives the initial parameters for the pyrolysis model and the fourth section gives the breakdown of the costs associated with this study.

D.1 Steel Water Network

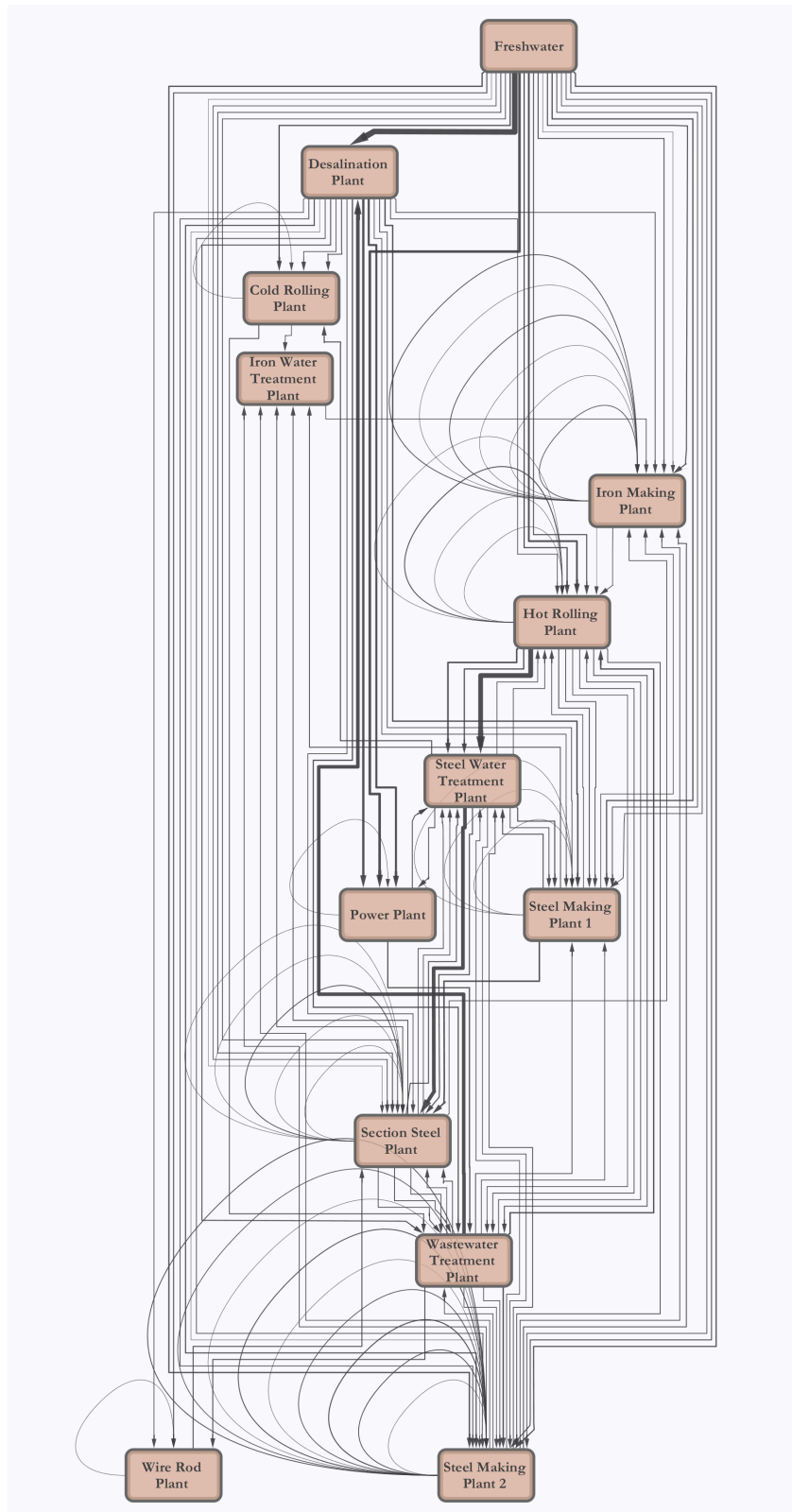


Figure 54. Unsimplified Steel Water Network

D.2 Universal Parameter Calculation

Table 44. Universal Parameter Calculation from Farzi, 2017

Table 1. Environmental Parameter Calculation from Farzi, 2017															
FARZI (2017)				Total Area of Experimental Wetland		0.82500 m ²									
				Experiment length		56.00000 days									
Designation from Study		Dry Wt. per plant		Dry Wt. of entire plant wetland per day (mg d ⁻¹)		% Chloride Removal of DW		Number of Observations		mg Cl ⁻ d ⁻¹		mg Cl ⁻ d ⁻¹ m ²		g Cl ⁻ d ⁻¹ m ²	
S. europaea	Salinity level of 10 dS m ⁻¹	30.20	g	8089.28	mg/d	31	% DW	8	2507.67	mg/d	3039.61	mg/d*m ²	3.039	g Cl ⁻ /d*m ²	
		2.07	std. error	554.46	std. error	3	std. error	8	297.38	std. error	360.46	std. error	0.360	std. error	
S. crassa	Salinity level of 10 dS m ⁻¹	33.70	g	9026.78	mg/d	21	% DW	8	1895.62	mg/d	2297.72	mg/d*m ²	2.297	g Cl ⁻ /d*m ²	
		2.51	std. error	672.32	std. error	1	std. error	8	167.57	std. error	203.12	std. error	0.203	std. error	
B. cycloptera	Salinity level of 10 dS m ⁻¹	34.30	g	9187.50	mg/d	23	% DW	8	2113.12	mg/d	2561.36	mg/d*m ²	2.561	g Cl ⁻ /d*m ²	
		2.15	std. error	575.89	std. error	2	std. error	8	226.51	std. error	274.56	std. error	0.274	std. error	
Dry Wt. per wetland (15 plants per wetland)		453.00 g (15 plants per wetland)													
		31.05 std. error													
		505.50 g													
		37.65 std. error													
		514.50 g													
		32.25 std. error													

Table 45. Universal Parameter Calculation for Rosema, 2016

Rosema (2016)										
	Designation from Study	Cl- (g/m²)	std. error	Cl- (mg/m²)	std. error	Days	mg Cl- /d*m²	std. error	g Cl- /d*m²	std. error
J. torreyi	JT-2	111.3	2	111300	2000	126	883.333	15.873	0.883	0.015
T. latifolia	TL-3	94.8	11	94800	11000	126	752.380	87.301	0.752	0.087

Table 46. Universal Parameter Calculation for Zhao, 2005

Zhao (2005)												
	Designation from Study	DW (kg hm⁻²)	std. error	DW (kg/m²)	std. error	% of DW Cl-	std. error	kg Cl-/m²	std. error	Growing Period (days)	g Cl-/d*m²	std. error
S. salsa		7700	539	0.77000	0.054	14.30	0.50	0.11011	0.00862	60	1.83517	0.14360
K. folium	Referenced as Kalidium folium	8700	652	0.87000	0.065	15.30	0.61	0.13311	0.01130	60	2.21850	0.18832

D.3 Initial Parameters for Pyrolysis Model

Table 47. Numerical Integration Initial Conditions

Equation	Initial Value	Parameters
B	1	A_1, E_1
B^+	0	$A_1, E_1, A_2, E_2, A_3, E_3$
G	0	A_2, E_2
C	0	A_3, E_3

The initial value for T_0 is 298 K according to Dzidzienyo et al. (2018). The values for n_1 , n_2 , n_3 , and R are constant and have the values 1, 1.5, 1.5, and $3.14E-3 \text{ kJ mol}^{-1} \text{ K}^{-1}$.

Temperature, when fitting thermogravimetric data with a constant heating rate follows the linear equation(Dzidzienyo et al., 2018; Koufopoulos et al., 1989):

$$T = \alpha t + T_0$$

Where:

α is the heating rate (W min^{-1})

t is the time (min)

and T_0 is the starting temperature (K)

Table 48. Parameter Estimation for Pyrolysis Model (95% Confidence Interval)

Parameter	Estimate	Standard Error
A1	13.1 min ⁻¹	.0322
E1	5.41 kJ mol ⁻¹	.0276
A2	16.91 min ⁻¹	.0346
E2	28.04 kJ mol ⁻¹	.0332
A3	12.79 min ⁻¹	.6683
E3	28.70 kJ mol ⁻¹	.1542

Table 49. Fitted Curve Statistics for Pyrolysis Model (95% Confidence Interval)

Fit Statistic	Value
Adjusted R ²	0.9998
AIC	-483.613
BIC	-467.485
R ²	0.9988

D.3 Pyrolysis Model Results

Table 50. Pyrolysis Model Results and Confidence Error Bands Results

Time	Observed Value	Modeled Value	STD Deviation	Temp	Lower Band	Upper Band 95% CI Single Prediction	Bottom Area	95% Confidence Interval
34.702	0.8643	0.8821	0.0010	471.51	0.8645	0.8996	0.8645	0.0351
35.725	0.8598	0.8720	0.0011	476.63	0.8544	0.8896	0.8544	0.0351
36.748	0.8540	0.8615	0.0011	481.74	0.8439	0.8791	0.8439	0.0351
37.771	0.8471	0.8505	0.0012	486.86	0.8329	0.8681	0.8329	0.0352
38.709	0.8398	0.8401	0.0012	491.55	0.8225	0.8577	0.8225	0.0352
39.562	0.8323	0.8304	0.0013	495.81	0.8128	0.8480	0.8128	0.0352
40.329	0.8238	0.8214	0.0013	499.64	0.8038	0.8391	0.8038	0.0352
41.011	0.8165	0.8133	0.0013	503.05	0.7957	0.8310	0.7957	0.0353
41.693	0.8088	0.8051	0.0014	506.46	0.7874	0.8227	0.7874	0.0353
42.375	0.8003	0.7967	0.0014	509.87	0.7790	0.8143	0.7790	0.0353
42.972	0.7934	0.7893	0.0014	512.86	0.7716	0.8069	0.7716	0.0353
43.568	0.7842	0.7818	0.0014	515.84	0.7641	0.7994	0.7641	0.0353
44.165	0.7766	0.7742	0.0014	518.83	0.7566	0.7919	0.7566	0.0353
44.762	0.7689	0.7666	0.0014	521.81	0.7489	0.7842	0.7489	0.0353
45.359	0.7607	0.7589	0.0014	524.79	0.7413	0.7766	0.7413	0.0353
45.956	0.7527	0.7512	0.0014	527.78	0.7335	0.7689	0.7335	0.0353
46.638	0.7449	0.7424	0.0014	531.19	0.7247	0.7600	0.7247	0.0353
47.320	0.7364	0.7335	0.0014	534.60	0.7158	0.7511	0.7158	0.0353
48.002	0.7280	0.7246	0.0014	538.01	0.7069	0.7423	0.7069	0.0353
48.684	0.7194	0.7157	0.0014	541.42	0.6981	0.7334	0.6981	0.0353
49.366	0.7112	0.7069	0.0014	544.83	0.6892	0.7245	0.6892	0.0353
50.133	0.7023	0.6969	0.0014	548.67	0.6793	0.7146	0.6793	0.0353
50.730	0.6947	0.6893	0.0014	551.65	0.6716	0.7069	0.6716	0.0353
51.441	0.6879	0.6802	0.0014	555.20	0.6625	0.6978	0.6625	0.0353
51.814	0.6805	0.6754	0.0014	557.07	0.6578	0.6931	0.6578	0.0353
52.605	0.6725	0.6654	0.0014	561.03	0.6478	0.6831	0.6478	0.0353
53.373	0.6641	0.6559	0.0013	564.86	0.6382	0.6735	0.6382	0.0353
54.055	0.6553	0.6475	0.0013	568.27	0.6299	0.6651	0.6299	0.0353
54.566	0.6485	0.6413	0.0013	570.83	0.6236	0.6589	0.6236	0.0352
55.163	0.6396	0.6341	0.0013	573.82	0.6165	0.6517	0.6165	0.0352
55.760	0.6303	0.6270	0.0013	576.80	0.6094	0.6446	0.6094	0.0352
56.374	0.6228	0.6199	0.0013	579.87	0.6022	0.6375	0.6022	0.0352
56.885	0.6150	0.6140	0.0013	582.43	0.5964	0.6316	0.5964	0.0352
57.328	0.6072	0.6089	0.0013	584.64	0.5913	0.6266	0.5913	0.0352
57.891	0.5982	0.6027	0.0013	587.46	0.5851	0.6203	0.5851	0.0352
58.386	0.5895	0.5972	0.0013	589.93	0.5796	0.6148	0.5796	0.0352
58.931	0.5803	0.5913	0.0013	592.66	0.5737	0.6089	0.5737	0.0352
59.426	0.5705	0.5861	0.0013	595.13	0.5685	0.6037	0.5685	0.0352
60.108	0.5611	0.5790	0.0013	598.54	0.5614	0.5966	0.5614	0.0352
60.790	0.5534	0.5720	0.0014	601.95	0.5544	0.5897	0.5544	0.0353
61.557	0.5459	0.5645	0.0013	605.79	0.5468	0.5821	0.5468	0.0352
62.495	0.5383	0.5555	0.0013	610.47	0.5379	0.5731	0.5379	0.0353

63.518	0.5323	0.5461	0.0014	615.59	0.5285	0.5638	0.5285	0.0353
64.541	0.5267	0.5372	0.0015	620.70	0.5195	0.5548	0.5195	0.0353
65.564	0.5210	0.5286	0.0015	625.82	0.5109	0.5463	0.5109	0.0354
66.587	0.5158	0.5205	0.0016	630.94	0.5028	0.5382	0.5028	0.0354
67.610	0.5103	0.5128	0.0017	636.05	0.4950	0.5305	0.4950	0.0355
68.633	0.5047	0.5054	0.0018	641.17	0.4876	0.5232	0.4876	0.0356
69.656	0.5002	0.4985	0.0018	646.28	0.4807	0.5163	0.4807	0.0356
70.679	0.4962	0.4919	0.0019	651.40	0.4741	0.5098	0.4741	0.0357
71.702	0.4922	0.4857	0.0020	656.51	0.4678	0.5036	0.4678	0.0358
72.725	0.4879	0.4799	0.0021	661.63	0.4620	0.4978	0.4620	0.0358
73.748	0.4842	0.4744	0.0021	666.74	0.4565	0.4923	0.4565	0.0359
74.771	0.4801	0.4692	0.0018	671.86	0.4515	0.4870	0.4515	0.0356
75.794	0.4763	0.4644	0.0029	676.97	0.4460	0.4828	0.4460	0.0367
76.817	0.4730	0.4598	0.0018	682.09	0.4420	0.4776	0.4420	0.0356
77.789	0.4694	0.4558	0.0016	686.95	0.4381	0.4735	0.4381	0.0354
78.864	0.4637	0.4516	0.0025	692.32	0.4334	0.4697	0.4334	0.0363
79.887	0.4588	0.4478	0.0034	697.43	0.4291	0.4666	0.4291	0.0374
80.910	0.4543	0.4443	0.0033	702.55	0.4257	0.4630	0.4257	0.0373
81.933	0.4497	0.4411	0.0046	707.66	0.4214	0.4607	0.4214	0.0393
82.956	0.4454	0.4380	0.0045	712.78	0.4184	0.4577	0.4184	0.0393
83.979	0.4410	0.4352	0.0041	717.89	0.4159	0.4545	0.4159	0.0386
85.002	0.4361	0.4325	0.0029	723.01	0.4142	0.4509	0.4142	0.0367
86.025	0.4315	0.4301	0.0029	728.12	0.4117	0.4484	0.4117	0.0367
87.048	0.4267	0.4277	0.0021	733.24	0.4098	0.4457	0.4098	0.0359
88.071	0.4220	0.4256	0.0025	738.35	0.4075	0.4437	0.4075	0.0362
89.094	0.4177	0.4236	0.0023	743.47	0.4055	0.4416	0.4055	0.0361
89.975	0.4148	0.4220	0.0022	747.87	0.4040	0.4400	0.4040	0.0360
91.311	0.4119	0.4197	0.0021	754.55	0.4018	0.4376	0.4018	0.0358
92.334	0.4100	0.4181	0.0023	759.67	0.4001	0.4361	0.4001	0.0360
93.357	0.4073	0.4166	0.0029	764.78	0.3982	0.4350	0.3982	0.0367
94.380	0.4047	0.4152	0.0035	769.90	0.3964	0.4340	0.3964	0.0376
95.403	0.4025	0.4139	0.0048	775.01	0.3940	0.4338	0.3940	0.0398

Table 51. Wetlands and Pyrolysis Calculations for Chloride Removal

Wetlands and Pyrolysis Calculations		
Influent into Salicornia Constructed Wetlands	Flowrate (m ³ h ⁻¹)	Cl ⁻ (mg L ⁻¹)
Desalination RO concentrate	110	800
Backwash WW	58	400
	Combined Flow (m ³ hr ⁻¹)	Combined concentration Cl ⁻ (mg L ⁻¹)
	168	661.904
	Maximum Wetland Area (m ²)	Combined concentration Cl ⁻ (mg d ⁻¹)
	746260	2668800000

Effluent out from Salicornia Constructed Wetlands	Salicornia Uptake (mg Cl⁻ d⁻¹ m⁻²)	
	3039.610	
	Salicornia Wetland Uptake (mg Cl⁻ d⁻¹)	Cl⁻ (mg L⁻¹) Concentration at outlet
	2268339649.350	99.320

Pyrolysis Char Generation from Salicornia Constructed Wetlands	dry weight per plant per day (g)	30% Char Yield from Pyrolysis of biomass (tonnes d⁻¹)
	0.539	2.195
	dry weight per wetland per day (g d⁻¹)	30% Char Yield from Pyrolysis of biomass (tonnes yr⁻¹)
	8.089	801.236
	dry weight per experimental wetland per day and area (g d⁻¹ m⁻²)	Annual Coal Consumption from Industry Partners (tonnes yr⁻¹)
	9.805	1050000
	dry weight per entire modeled wetland per day and area (tonnes d⁻¹)	Percent of Coal Reduced by Pyrolysis (%)
	7.317	0.07631

Table 52. Uptake Calculation for Different Plant Species

Uptake Calculation						
Plant Species	growth rate in dry weight (g) of plant per area(m ²) and day (d)	std error	kg DW m ⁻²	days	Area (m ²)	plants
S. europaea	9.805	0.55446				
S. crassa	10.942	0.67232				
B. cycloptera	11.136	0.57589				
J. torreyi	36.360	0.1076	4.581	126	0.117	2
T. latifolia	29.714	0.8014	3.744	126	0.117	2
S. salsa	12.833	0.05390				
K. folium	14.500	0.06520				

D.4 ENA Model Networks

Table 53. Steel Water Network Without Wetlands

		To													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
From	1 Imports	0	115.260	1078.333	1154.407	130.750	405.805	79.341	150.224	312.128	0	0	53.500	0	0
	2 Cold Rolling Plant	0	0	0	0	0	0	0	0	0	45.709	0	0	0	200.234
	3 Desalination Plant	0	53.118	0	15.562	20.000	643.549	15	182.506	146.604	170.596	0	10.000	0	449.025
	4 Hot Rolling Plant	0	0	0	0	0	0	0	57.550	31.173	1276.675	0	0	0	0
	5 Iron Making Plant	0	0	0	4.345	0	0	0	0	0	0	0	0	0	232.168
	6 Powerplant	0	0	0	0	0	0	0	0	0	151.890	0	0	0	942.085
	7 Section Steel Plant	0	0	0	0	10	0	0	0	0	236.445	0	0	0	840.772
	8 Steel Making Plant 1	0	0	0	7.591	2.054	0	170	0	0	101.260	0	0	0	251.066
	9 Steel Making Plant 2	0	0	0	0	70.000	0	0	0	0	74.210	0	0	0	502.692
	10 Wastewater Treatment Plant	0	77.564	627.627	183.493	3.709	44.622	761.598	141.691	156.998	0	0	59.483	0	0.000
	11 Wetlands	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	12 Wire Rod Plant	0	0	0	0	0	0	61.278	0	0	0	0	0	0	61.705
	13 Exports	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	14 Dissipations	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 54. Steel Water Network with Wetlands

		To													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
From	1 Imports	0	91.073	1078.333	112.653	108.684	719.000	26.727	122.844	174.332	0	0	164.192	0	0
	2 Cold Rolling Plant	0	0	0	0	0	0	0	0	0	0.303	0	0	0	40.000
	3 Desalination Plant	0	42.000	0	96.018	20.000	350.000	30.091	155.000	124.407	105.561	330.000	10	0	73.136
	4 Hot Rolling Plant	0	0	0	0	0	0	0	104.668	17.975	0.769	0	0	0	65.960
	5 Iron Making Plant	0	0	0	0	0	0	0	1.035	5.462	0.006	0	0	0	371.149
	6 Powerplant	0	0	0	0	0	0	0	0	0	1.586	0	0	0	795.000
	7 Section Steel Plant	0	0	0	4.941	0	0	0	0	0	98.708	0	0	0	89.015
	8 Steel Making Plant 1	0	0	0	0	7.468	0	10.862	0	0	0.156	0	0	0	1.198
	9 Steel Making Plant 2	0	0	0	4.200	65.178	0	8.094	4.822	0	0.296	0	0	0	0.625
	10 Wastewater Treatment Plant	0	0.100	257.881	0.715	0.299	0.787	116.889	0.374	0.374	0	0	21.351	0	109.704
	11 Wetlands	0	0.040	0	0.003	0.016	0.319	0	0.050	0.135	0	0	8.656	0	0
	12 Wire Rod Plant	0	0	0	0	0	0	0	170.000	0	34.200	0	0	0	0
	13 Exports	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	14 Dissipations	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 55. Current Chinese Steel Industry Material, Water, and Energy Meta-Model

		To																
From		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
	0	Imports	0	1.2346	0	0	0.6904	0.1300	0.075	1.0123	0	4.8052	0	0	0	0	0	0
	1	Coking Plant	0	0	0	0	0.3173	0.0076	0.0013	0.0538	0	0	0	0	0	0	0.004	0.8510
	2	Cold Rolling Plant	0	0	0	0	0	0	0	0.015	0.002	0.303	0	0	0	0	0.1923	0
	3	Hot Rolling Plant	0	0	0	0	0	0	0	0	0.073	0.769	0	0	0	0	0.4827	0.2536
	4	Iron Plant	0	0	0	0	0	0.0067	0.0477	0	1.0096	0.006	0	0	0	0	0	1.8633
	5	Lime Plant	0	0	0	0	0	0	0	0.0635	0.0808	0	0	0	0	0	0	0
	6	On-Site Power Plant	0	0	0.0562	0.0936	0	0	0	0	0	0.1788	0.0318	0.0431	0	0	0	0
	7	Sinter Plant	0	0	0	0	1.2365	0	0	0	0	0	0	0	0	0	0	0.0422
	8	Steel Plant	0	0	0.1950	0.5600	0	0	0.029	0	0	0.452	0.2450	0	0	0	0	0.2983
	9	Water Treatment Plant	0	0	0.2616	0.9249	0.6722	0	0.2510	0.0927	0.5666	0	0	0	0	0	0.13	3.6157
	10	Wide & Heavy Plate Plant	0	0	0	0	0	0	0	0.041	0.021	0	0	0	0	0	0.2000	0.0146
	11	Oxygen Plant	0	0	0	0	0.0171	0	0	0	0.0260	0	0	0	0	0	0	0
	12	Wetlands	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	13	Pyrolysis	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	14	Exports	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	Dissipation	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

Table 56. Best Case Chinese Material, Water, Energy Steel Manufacturing Meta-Model

		To															
		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
From	Imports	0	0.6173	0	0	0.6862	0.1300	0.958	0.9717	0	3.7080	0	0	0	0	0	0
	Coking Plant	0	0	0	0	0.3173	0.0076	0.0013	0.0538	0	0	0	0	0	0	0.038	0.2226
	Cold Rolling Plant	0	0	0	0	0	0	0	0.015	0.002	0.303	0	0	0	0	0.0603	0
	Hot Rolling Plant	0	0	0	0	0	0	0	0	0.073	0.769	0	0	0	0	0.4267	0.085
	Iron Plant	0	0	0	0	0	0.0067	0.0477	0	1.0096	0.006	0	0	0	0	0	1.5534
	Lime Plant	0	0	0	0	0	0	0	0.0635	0.0808	0	0	0	0	0	0	0
	On-Site Power Plant	0	0	0.0455	0.0758	0	0	0	0	0	1.5855	0.0258	0.0349	0.374	0	0	0
	Sinter Plant	0	0	0	0	1.2365	0	0	0	0	0	0	0	0	0	0	0.0012
	Steel Plant	0	0	0.195	0.5600	0	0	0.029	0	0	0.452	0.2500	0	0	0	0	0.644
	Water Treatment Plant	0	0	0.1	0.7148	0.2990	0	0.7866	0.0927	0.7475	0	0	0	0.5782	0	3.391	0.1300
	Wide & Heavy Plate Plant	0	0	0	0	0	0	0	0.041	0.006	0	0	0	0	0	0.229	0
	Oxygen Plant	0	0	0	0	0.0012	0	0	0	0.0260	0	0	0	0	0	0	0.008
	Wetlands	0	0	0.0404	0.0031	0.0159	0	0.319	0	0.1846	0.015	0	0	0	0.0910	0	0.283
	Pyrolysis	0	0.0235	0	0	0.068	0	0	0	0	0	0	0	0	0	0	0
	Exports	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Dissipation	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

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